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Driving or driven by others? A dynamic perspective on how data-driven start-ups strategize across different network roles in digitalized business networks

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ABSTRACT

Digitalization transforms how actors conduct activities and exchange resources in business networks. Data-driven start-ups are key actors in this transformation as they are often the first to commercialize novel digital technologies and influence business networks through their strategizing. Extant Industrial Marketing & Purchasing (IMP) literature has investigated roles and strategizing in business networks. However, understanding how data-driven start-ups' specificities impact their roles and strategizing is still at its infancy. Specifically, the authors conceptually show that assumptions on how data-driven start-ups strategize contradict strategizing tenets of prior IMP literature. Therefore, previous knowledge on strategizing needs further differentiation. Addressing this research need, theories-in-use and multiple case study research on 23 data-driven start-ups is conducted to examine (1) in what network roles they operate and (2) how they strategize within and across different network roles. The study extends IMP and data-driven business model research by identifying four network roles (enabler, extender, transformer, orchestrator) and developing a specific classification framework for data-driven start-ups. Furthermore, the study shows that IMP tenets apply in specific network roles only to some extent to data-driven start-ups. Finally, three strategizing trajectories are identified, which provide a dynamic perspective to IMP literature for guiding entrepreneurs on strategizing opportunities.

1. Introduction

The emerging digitalization of society and the economy is transforming how companies conduct activities, use resources, and manage relationships among different actors in business networks (Möller, Nenonen, & Storbacka, 2020; Pagani & Pardo, 2017; Ritter & Pedersen, 2020). Thus, Industrial Marketing & Purchasing (IMP) research, which in the past has focused on how business networks and their actors evolve and transform (Håkansson, 1982; Håkansson & Snehota, 1995), provides a highly relevant foundation to study this change (Pagani & Pardo, 2017). Business networks' digitalization is largely fueled by data-driven start-ups, which are often the first to commercialize new ideas through innovative data-driven business models based on digital technologies and data as their key resource (Hartmann, Zaki, Feldmann, & Neely, 2016). Accordingly, we define data-driven start-ups as start-ups that create and capture value through data-based activities (e.g., data aggregation, processing, or analytics), thereby linking dispersed resources and actors. In doing so, data-driven business models potentially equip data-driven start-ups with the capabilities to change existing business networks and create new business opportunities (Fehrer et al., 2020; Nenonen, Storbacka, & Windahl, 2019). Indeed, by digitalizing business networks, data-driven start-ups can drive and transform not only individual firms and their relationships, but also entire industries rapidly (Kumaraswamy, Garud, & Ansari, 2018).

Digitalized business networks are characterized by complex relationships, close cooperation, and fast-moving, data-driven interactions between different actors (Peppard & Rylander, 2006). These characteristics are challenging for data-driven start-ups and lead to high failure rates, particularly in the early stages (Giardino, Wang, & Abrahamsson, 2014). The reason for failure is often inappropriate strategizing that

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focuses on trying to imitate the few successful start-ups that have become driving actors (Aaboen, Laage-Hellman, Lind, Öberg, & Shih, 2016), instead of acting in another role that may better fit the data-driven start-up's initial network position or key resource access. Thus, it is crucial for founders to understand network dynamics and strategize accordingly to position their data-driven start-up appropriately in digitalized business networks vis-à-vis incumbent actors, acquire critical resources, and achieve the desired network role (Lamine, Fayolle, Jack, & Byrne, 2019; Pagani & Pardo, 2017). In this regard, we understand strategizing to be a proactive and purposeful activity that may change the actor's network position or the strength of relationships or ties (these terms are used as synonyms), ultimately resulting in a shift from one network role to another (Elfring & Hulsink, 2003; Laari-Salmela, Mainela, & Puhakka, 2019).

Despite data-driven start-ups' increasing relevance and proliferation, prior research does not account for these issues. Although IMP literature, which traditionally has investigated incumbent firms, increasingly has shifted attention to start-ups in recent years (Aaboen, La Rocca, Lind, Perna, & Shih, 2017; Baraldi, Havenvid, Linné, & Öberg, 2019; Snehota, 2011), the start-ups studied predominantly are from non-data-driven or blended contexts (McGrath, Medlin, & O'Toole, 2019; Oukes, von Raesfeld, & Groen, 2019). Moreover, studies on start-ups' network positions and roles have deduced their insights merely from the resource level, adopting a rather static network role perspective (Aaboen et al., 2016; Guercini & Runfola, 2015) and potentially leading to an incomplete understanding of the dynamics that data-driven start-ups face in digitalized business networks. Therefore, we argue that existing research is challenged in several ways, including the question of whether existing IMP knowledge remains applicable in the context of digitalized business networks.

The following example illustrates the difficulties in accounting for the new dynamics of strategizing in data-driven contexts outlined in the literature on data-driven business models and digital business strategies compared to existing knowledge from IMP research. Recent IMP studies state that start-ups enter pre-existing network structures in a more peripheral network position and, therefore are driven by more centrally located actors (Snehota, 2011). However, studies on data-driven business models and digital business strategy show that data-driven start-ups can take central network positions and drive other actors in early stages by creating a large number of new bonds between previously unconnected actors through digital platforms (Pagani, 2013; Parker, van Alstyne, & Choudary, 2016). This contradiction indicates that data-driven start-ups in digitalized business networks tend to drive other actors, rather than being driven by them. However, it remains unknown under which conditions and in which network roles data-driven start-ups can and cannot be drivers. Evidently, digitalization and data-driven business models change the playing field and impact relationships in such a fundamental way that IMP knowledge must be broadened to explain data-driven start-ups' roles and their strategizing in digitalized business networks (Ritter & Pedersen, 2020).

Therefore, we aim to answer the following research questions: (1) What roles do data-driven start-ups take in digitalized business networks? (2) How do data-driven start-ups dynamically strategize within and across different network roles on various strategic trajectories in digitalized business networks?

To address our research questions, we carefully review IMP literature on start-ups and derive four tenets for start-up strategizing in non-data-driven settings, contrasting them with tenets documented in the fast-growing literature on data-driven business models and digital business strategy. Our overview of these contradictions serves as the foundation for adopting theories-in-use and explorative multiple case study research to better understand the various nuances of data-driven start-ups' strategizing in different network roles. Theories-in-use is particularly suitable for our study, as network roles and strategizing emerge from founders' mental models, i.e., individual interpretations of how to address and proactively shape change in digitalized business networks (Laari-Salmela et al., 2019). In our study, we therefore adopt the perspective of the individual founder. This approach is then embedded in multiple case study research that enables aggregation and contextualization of the individual perspectives at the firm level across multiple cases. In total, we investigate 23 data-driven start-ups and interview their founders to discover in which network role they act, how their strategizing varies from non-data-driven start-ups in different network roles, and which dynamic strategizing trajectories they follow in digitalized business networks.

Based on our analysis, we make the following three contributions: First, by identifying four network roles of data-driven start-ups (extender, enabler, transformer, orchestrator), we add the digitalization perspective to IMP literature on start-ups (Baraldi et al., 2019) and network roles (Aaboen et al., 2016). Thereby, we use the Activity-Resource-Actor (ARA) model and data-driven business model components to include not only the resource level, but also a nuanced activity and actor perspective, to build a classification framework that provides a comprehensive picture of data-driven start-ups' possible network roles. We demonstrate that specifically, the strength of network ties to access data and the network position are key variables in strategizing in complex and interdependent digitalized business networks. Second, we put the network roles in the context of our elaborated contradictions, extending previous IMP literature (Baraldi, La Rocca, Perna, & Snehota, 2020) by finding data-driven start-ups' strategizing in specific network roles needs to be studied on the basis of different assumptions compared with previous IMP studies. Third, based on our classification framework, we spotlight to the importance of a dynamic perspective in digitalized business networks by examining data-driven start-ups not only at a specific point in time, but also across three identified main strategizing trajectories that they follow. By identifying the awareness of the extent to which network roles change as being key to success in digitalized business networks, we contribute to previous IMP studies on strategizing (Aaboen et al., 2016; Baraldi, Brennan, Harrison, Tunisini, & Zolkiewski, 2007) and address Möller et al.'s (2020) argument that emphasizes the importance of purposeful strategizing in highly dynamic digitalized business networks.

The remainder of our paper is structured as follows. In Section 2, we lay out our study's theoretical foundation, describing key concepts from IMP literature, outlining the strategizing tenets derived from existing IMP literature on start-ups, and contrasting them with the strategizing tenets from literature on data-driven business models and digital business strategy. In Section 3, we explain the applied methodology. Section 4 reveals our study's results. In Section 5, we discuss our results and provide implications for academia and management. Furthermore, we outline our study's limitations and provide suggestions for future research.

2. Theoretical foundation

Our study's theoretical foundation is based on two literature streams: (1) IMP literature mainly focusing on non-data-driven (traditional) start-ups and (2) literature on data-driven business models and digital business strategy (DDBM).[1] We first describe our study's relevant key IMP concepts: *network position*; *network role*; and *strategizing*. In the second step, we demonstrate how insights from the DDBM literature challenge widely accepted strategizing tenets from IMP literature. Fig. 1 illustrates the four elaborated contradictions and serves as this chapter's structural body.

[1] In the following, we will describe both literature streams "data-driven business models" and "digital business strategy" in a more simplistic manner using the acronym DDBM.

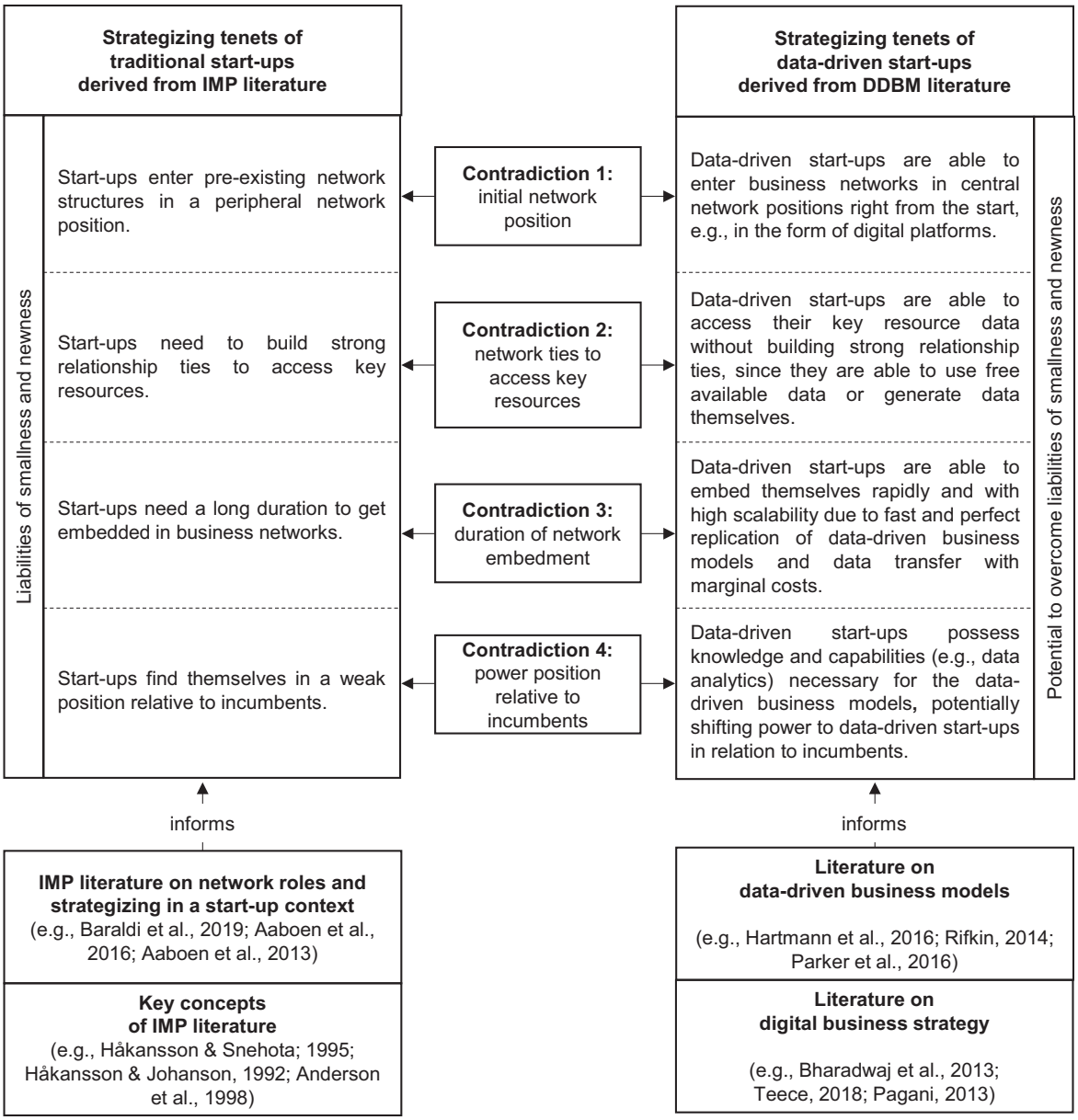

Fig. 1. Contrasting strategizing tenets of traditional vs. data-driven start-ups from IMP and DDBM literature.

2.1. Key concepts and start-ups in IMP literature

2.1.1. Key concepts in IMP literature

Business networks are understood as a "set of two or more connected business relationships, in which each exchange relation is between business firms that are conceptualized as collective actors (Emerson, 1981)." (Anderson, Håkansson, & Johanson, 1994, p. 2). Being at the core of every business network, relationships are interaction processes in which two actors combine, exchange, or create resources in an activity with mutual orientation and commitment (Håkansson & Johanson, 1992; Håkansson & Snehota, 1995). The higher (lower) the level of interaction intensity and diversity between the actors, the stronger (weaker) the ties and, thus the exchange of fine-grained information or trust-based governance (Elfring & Hulsink, 2003; Rowley, Behrens, & Krackhardt, 2000).

Based on the Activity-Resource-Actor (ARA) model (Håkansson & Johanson, 1992; Håkansson & Snehota, 1995) – which spotlights activity links, resource ties, and actor bonds –, researchers increasingly take a dynamic perspective and investigate how firms connect with other actors and manage relationships in business networks (Aaboen, Holmen, & Pedersen, 2017). Activities can be for example "offering a product or service" or "building strong ties to suppliers". Several interlinked activities form a transaction chain, which is directed toward a purpose (e.g., reaching a certain network role). Resources can be tangible (e.g., equipment or manpower) or intangible (e.g., knowledge or data) and are heterogenous and controlled by one or more actors. Actors are individuals or companies, since both are able to set priorities leading to a purpose while interacting (Håkansson & Johanson, 1992; Schepis, Purchase, & Ellis, 2014). The dynamic purpose building based on activities, resources, and actors is closely linked to three key concepts, namely *network position*, *network role* and *strategizing*.

In IMP literature, *network position* is determined by the location in the business network relative to other actors (Anderson, Havila, Andersen, & Halinen, 1998). For instance, when an actor has a large number of ties to others or controls critical resources (e.g., knowledge or interfaces between buyer and seller), it increases network control and could be assigned a more central network position (Bizzi & Langley, 2012; Håkansson & Johanson, 1992) that may lead to better firm performance

(Fund, Pollock, Baker, & Wowak, 2008). *Network roles* are intertwined closely with network positions, as they reflect how an actor interprets its network position (Abrahamsen, Henneberg, & Naudé, 2012), making network role identification highly dependent on the perspective taken. Generally, a focal actor dynamically acts in a role, but statically holds a position (Anderson et al., 1998). The process of how actors make sense of their network positions and roles is referred to as *strategizing*. Laari-Salmela et al. (2019) describe strategizing as an "ongoing effort that follows the routinized ways of both proactively making moves to find future direction for the development of the firm as well as reacting to changes in the network" (p. 201). This may involve alterations in network positions or changes in the degree of relationship strength with key resource-providing actors in the business network (Aaboen et al., 2016; Elfring & Hulsink, 2003), potentially leading to a change in the associated role.

2.1.2. Start-ups in business networks according to IMP literature

In recent years, several studies have emerged in IMP literature that focus on start-ups in business networks and place the key concepts described above in a new light. Start-ups exhibit unique characteristics due to their significantly different size and age compared with incumbents (Aldrich Howard & Ruef, 2006; Su, Xie, & Li, 2011; Zaremba, Bode, & Wagner, 2016), often referred to as *liability of smallness* and *liability of newness*, conveying that start-ups have limited access to resources and capabilities, e.g., financial, human, and technological capital (Aldrich & Auster, 1986) or lack legitimacy, track records, and effective networks (Stinchcombe, 1965). Based on these liabilities, start-ups strategize and act considerably differently than incumbents (Baraldi et al., 2019). For instance, start-ups need to adapt their offerings to existing network structures due to their peripheral network position or lack of key resources, which can impact their power position negatively. According to a recent literature review on start-ups in IMP research of Baraldi et al. (2019), previous studies in examining these differences focus predominantly on how start-ups create a position in established business network structures, how they acquire, develop, or combine resources with other actors, and how they may influence or change existing network structures. In particular, the process of initiating ties with other actors is usually at the center of research interest, as such ties represent crucial assets and liabilities for the further development of the individual start-up (e.g., ties to access key resources) (Baraldi et al., 2020).

However, most of these studies investigate start-ups that produce physical products, such as wireless communication devices (McGrath et al., 2019) and medical products (Oukes et al., 2019). Furthermore, they base their findings on a mixture of start-ups from different industries with diverse business models (Brown, Mawson, & Rowe, 2019; Diánez-González & Camelo-Ordaz, 2019) or examine start-ups emerging from specific contexts, such as academia (Aaboen et al., 2016; Guercini & Milanesi, 2019; Landqvist & Lind, 2019). Therefore, it remains unclear, and of high interest to both IMP researchers and managers, whether these findings also apply to data-driven start-ups, as they might strategize differently depending on their role within the digitalized business network.

2.2. Contradictions between traditional start-ups' strategizing tenets from IMP literature and data-driven start-ups' tenets from DDBM literature

Insights from IMP literature on how start-ups strategize in business networks differ from data-driven start-ups' tenets derived from DDBM literature, comprising data-driven business models (Hartmann et al., 2016) and digital business strategy (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013) literature streams. For instance, DDBM literature suggests that data enable data-driven start-ups to form and commercialize data-driven business models in a short period of time (Bharadwaj et al., 2013; Hartmann et al., 2016), thereby shaping and driving other actors and their relationships in digitalized business networks. This view is closely related to recent market-shaping literature, which states that digital platforms can re-configure whole networks by generating new resource linkages (Fehrer et al., 2020; Nenonen et al., 2019). Since data-driven start-ups usually focus on a specific data-driven business model, we describe the components of data-driven business models developed by Hartmann et al. (2016) in more detail to illustrate the basis on which data-driven start-ups determine their strategizing: (1) key resource, (2) key activities, (3) offering, (4) customer segment, (5) revenue model, and (6) cost structure. Key resources can be internal or external (big) data, often freely available and easy to access, combined with data-related domain knowledge (e.g., big data analytics, cloud computing) or key partnerships. Relative to the respective key resource of data, each data-driven start-up performs several key activities, such as data aggregation, analysis, or visualization, leading to the creation of an offering or value proposition. The offering may take the form of data (e.g., crawled raw data), information (e.g., analyzed data), or data-enriched physical products (e.g., smart lock). The customer segment describes the desired target group of the data-driven start-up's offering, e.g., B2B and/or B2C customers. The revenue model determines how the data-driven start-up generates its income. Typical examples include subscription-, advertising-, or transaction-based models. The cost structure strongly depends on how costly it is to access the key resource of data. For example, if the data is generated internally, there is no cost for additional data collection and the analytics services can be provided at a marginal cost of almost zero, resulting in a specific cost advantage for fast and high growth. Therefore, these specific characteristics of data-driven business models might enable data-driven start-ups to strategize differently compared to traditional start-ups.

Based on a careful review of IMP literature on traditional start-ups and DDBM literature on data-driven start-ups, we derive four contradictions that are related to (1) initial network position, (2) network ties to access key resources, (3) duration of network embedment, and (4) power position relative to incumbents.

2.2.1. Contradiction 1: initial network position

Prior IMP research has suggested that traditional start-ups need to fit their solutions fully into pre-existing network structures and adapt to incumbent actors that already occupy the respective network's center (Håkansson & Waluszewski, 2007; Snehota, 2011). This creates the need for strategic actions to gain central actors' acceptance and expand their business (La Rocca & Perna, 2014). For instance, IMP researchers have argued that start-ups may monitor their limited set of existing relationships to acquire additional ties that fuel their success (Aaboen, Holmen, & Pedersen, 2017), or may undertake measures to adjust their business networks and structure to their advantage (Baraldi et al., 2019). This allows start-ups to overcome inertia in inherently stable existing business networks (Baraldi et al., 2019), thereby moving from an initially peripheral network position to the center. Altogether, we conclude that IMP research states that start-ups tend to enter pre-existing network structures in a more peripheral network position.

Contradicting this tenet, insights from DDBM literature (Bharadwaj et al., 2013; Hartmann et al., 2016; Pagani, 2013) suggest that data-driven start-ups can establish themselves in business networks in central positions from the beginning as they create new direct and indirect ties between a large number of actors. For instance, data-driven start-ups typically draw on multiple data sources, leading to many actors' involvement. Furthermore, fast-paced technology shifts confront actors with an increasing number of attractive opportunities for new entrants (Bharadwaj et al., 2013; Teece, 2018), potentially leading to the creation of new bonds with previously unconnected actors. In particular, data-driven start-ups that connect a large set of actors (e.g., electronic marketplaces or housing platforms) are key to coordinating value cocreation and appropriation in digitalized environments (Nambisan, Lyytinen, Majchrzak, & Song, 2017). Through the creation of direct and indirect network effects, they can reach enormous growth rates in terms of actor numbers and value (Shapiro & Varian, 1999). These so-called digital

platforms (Parker et al., 2016) can occupy customer interfaces immediately after entering business networks and alter existing relationships to their advantage (Andersson & Mattsson, 2016) while breaking traditional industry boundaries and defining new ones (Bharadwaj et al., 2013).

2.2.2. Contradiction 2: network ties to access key resources

IMP studies on business relationship initiations and resource combinations indicate that traditional start-ups do not own or control all required resources (Ciabuschi, Perna, & Snehota, 2012). Accordingly, start-ups need to interact with other actors in the network to acquire key resources (Håkansson, Ford, Gadde, Snehota, & Waluszewski, 2009), resulting in a greater vulnerability than incumbents (La Rocca, Perna, Snehota, & Ciabuschi, 2019). Following this argumentation, start-ups need to build initial relationships (Aaboen, Dubois, & Lind, 2013) or alliances (Callon, 1986) based on strong ties to secure reliable access to valuable resources, e.g., through close supplier relationships (La Rocca et al., 2019). Overall, start-ups need to develop strong network ties with other actors to access key resources and strategize successfully (Baraldi et al., 2020).

However, we argue data-driven start-ups can access data as their key resource directly and without strong ties in two ways: First, data-driven start-ups can acquire freely available data through open application programming interfaces, e.g., in the context of governmental or social network data (Hartmann et al., 2016) that are viewed as important resources for many data-driven start-ups and their strategizing (Lakomaa & Kallberg, 2013). Strong and trusting ties with free data providers are not of high importance, as these providers usually are interested in the widest possible data dissemination to get analyzed by third parties. Second, data-driven start-ups can generate data internally by themselves via their own smart physical products or digital services, e.g., smartphone apps or smart devices. These self-generated data then can be used for further digital services (Porter & Heppelmann, 2014). Therefore, data-driven start-ups hold a major advantage over asset-heavy start-ups that solely produce physical products, as they can acquire key resources (data) at marginal costs and in unidirectional relationships without a distinct exchange character. Even in the few cases in which data-driven start-ups use their own physical components to generate their data, production of simple hardware components often is outsourced to contract manufacturers on a large scale, significantly reducing hardware management complexities (Berg, Birkeland, Nguyen-Duc, Pappas, & Jaccheri, 2020). However, all data need to be prepared and enriched, as such data contain no value per se (Janssen, Charalabidis, & Zuiderwijk, 2012). Therefore, we draw the conclusion that the exploitation of freely available or self-generated raw data shifts data-driven start-ups' focus toward how to create value on the customer end, rather than how to access data.

2.2.3. Contradiction 3: duration of network embedment

When traditional start-ups enter business networks and build initial relationships, IMP researchers argue that these start-ups are confronted with a lack of legitimacy among existing actors (Elfring & Hulsink, 2003; La Rocca et al., 2019), generally hindering their ability to be perceived as meaningful, predictable, and trustworthy actors (Suchman, 1995), and limiting acceptance and support from other actors operating in the same business network (La Rocca et al., 2019). The start-ups' legitimacy within the corporate network is particularly important regarding their production and logistics activities, as they require trusting relationships with potential suppliers. In cases when the start-ups decide to take on these functions internally, large investments and complex implementation processes often are involved (La Rocca et al., 2019). Therefore, the strategizing process of business network embedment often takes a long time, as it includes time-consuming linkage of the start-up's own position and role to other actors' agendas and interpretations (Håkansson & Waluszewski, 2007; Havenvid & La Rocca, 2017).

However, data-driven start-ups can establish themselves rapidly and with high scalability, mainly because of data-driven business models' characteristics, as they are considerably different from those of non-data-driven ones (Amit & Han, 2017; Zott, Amit, & Massa, 2011). Unlike traditional business models that may rely on tangible assets, e.g., production facilities or logistics, data-driven business models are based on the following specificities: (1) marginal costs close to zero for duplication; (2) perfectly possible replication; and (3) availability almost anywhere in the world (McAfee & Brynjolfsson, 2017; Rifkin, 2014). Thus, data-driven business models significantly reduce transaction costs, enabling data-driven start-ups to realize fast speed to market and business growth (Huang, Henfridsson, Liu, & Newell, 2017; Peppard & Rylander, 2006). For instance, data-driven start-ups that develop smartphone applications can adapt rapidly to different platforms' technical requirements and customer attractiveness (Bharadwaj et al., 2013), thereby increasing growth potential. Overall, we argue that digitalization leads to an acceleration in relationship formation and dynamics, allowing data-driven start-ups to become established in business networks more quickly.

2.2.4. Contradiction 4: power position relative to incumbents

IMP literature posits that successfully establishing a position in business networks often requires alliances with incumbent actors that already are positioned at the center of business networks (Baum, Calabrese, & Silverman, 2000), as incumbents possess more critical resources and competencies, particularly in non-technical aspects of the underlying relationship (Oukes et al., 2019), e.g., important customer or supplier contacts. However, it is often difficult to build relationships with incumbents, as start-ups lack customer track records or do not have a clear organization yet (Havenvid & La Rocca, 2017; La Rocca, Ford, & Snehota, 2013). This holds implications for the structural power base, which essentially involves assuming that power is derived from control over critical resources that other actors need (Pfeffer & Salancik, 1978) and the organization's position in a network (Kähkönen & Virolainen, 2011; Pfeffer, 2009). Considering that start-ups typically lack these critical resources and often cannot leverage their physical product know-how, they find themselves in a weak bargaining position relative to incumbent actors (Oukes et al., 2019).

This contrasts with data-driven start-ups, which can gain power related to incumbents significantly by leveraging their inherent data-specific knowledge, such as data aggregation or analytics (Ardolino et al., 2018). Therefore, in addition to data themselves, the ability to process these data comprises a key resource and may shift power toward actors with such abilities (Coreynen, Matthyssens, Vanderstraeten, & van Witteloostuijn, 2020). In particular, incumbents often lack the necessary expertise to exploit data, making them reliant on collaborations with data-driven start-ups (Kupp, Marval, & Borchers, 2017). Therefore, many incumbents shift their focus toward data-driven start-ups to use their knowledge to differentiate themselves from competitors, thereby maintaining and expanding competitive advantage (Jordanius, Juell-Skielse, & Kailas, 2019). In the past, start-ups tended to drive interest in business relationships between incumbents and start-ups unilaterally, creating corresponding hurdles (Gardet & Fraiha, 2012). This may no longer be true for data-driven start-ups, as the incumbents' lack of data-driven capabilities makes potential collaborations more likely to be based on mutual interests. For instance, incumbents have been establishing a large number of corporate venture client and capital departments, such as BMW Startup Garage or Siemens next47 that aim to partner with start-ups, especially in the digital environment. Therefore, we argue that this phenomenon highlights incumbents' need to "market themselves" to coveted data-driven start-ups, potentially placing them in a higher power position relative to incumbents.

Based on our derived contradictions, we conclude that data-driven start-ups may strategize differently compared with traditional start-ups depending on their network role in digitalized business networks. Therefore, findings from previous IMP studies regarding start-ups' network roles and strategizing may not be applicable to data-driven

start-ups. Specifically, we argue that data-driven start-ups may have the ability to influence and drive entire digitalized business networks. However, this influence is highly context-specific (Nenonen et al., 2019). Potentially, network configurations exist, where data-driven start-ups might be more driven by incumbents rather than being their drivers. The question of "being driven by" or "driving" others might particularly depend on the data-driven start-ups' network role, which is influenced by its initial network position, the strength of ties needed to access data as its key resource, the time needed to get established, or the power position toward incumbents. Therefore, we aim to fill the gap in IMP literature by investigating (1) which network roles data-driven start-ups take in digitalized business networks and (2) how they dynamically strategize within and across different network roles on strategic trajectories in digitalized business networks. In particular, we investigate how and in which network roles the data-driven start-ups' strategizing differs in the light of the identified contradictions as well as which dynamic strategizing trajectories they follow.

3. Methodology

3.1. Research design

With the commercialization of new data-driven business models, data-driven start-ups are key actors in the digitalization of business

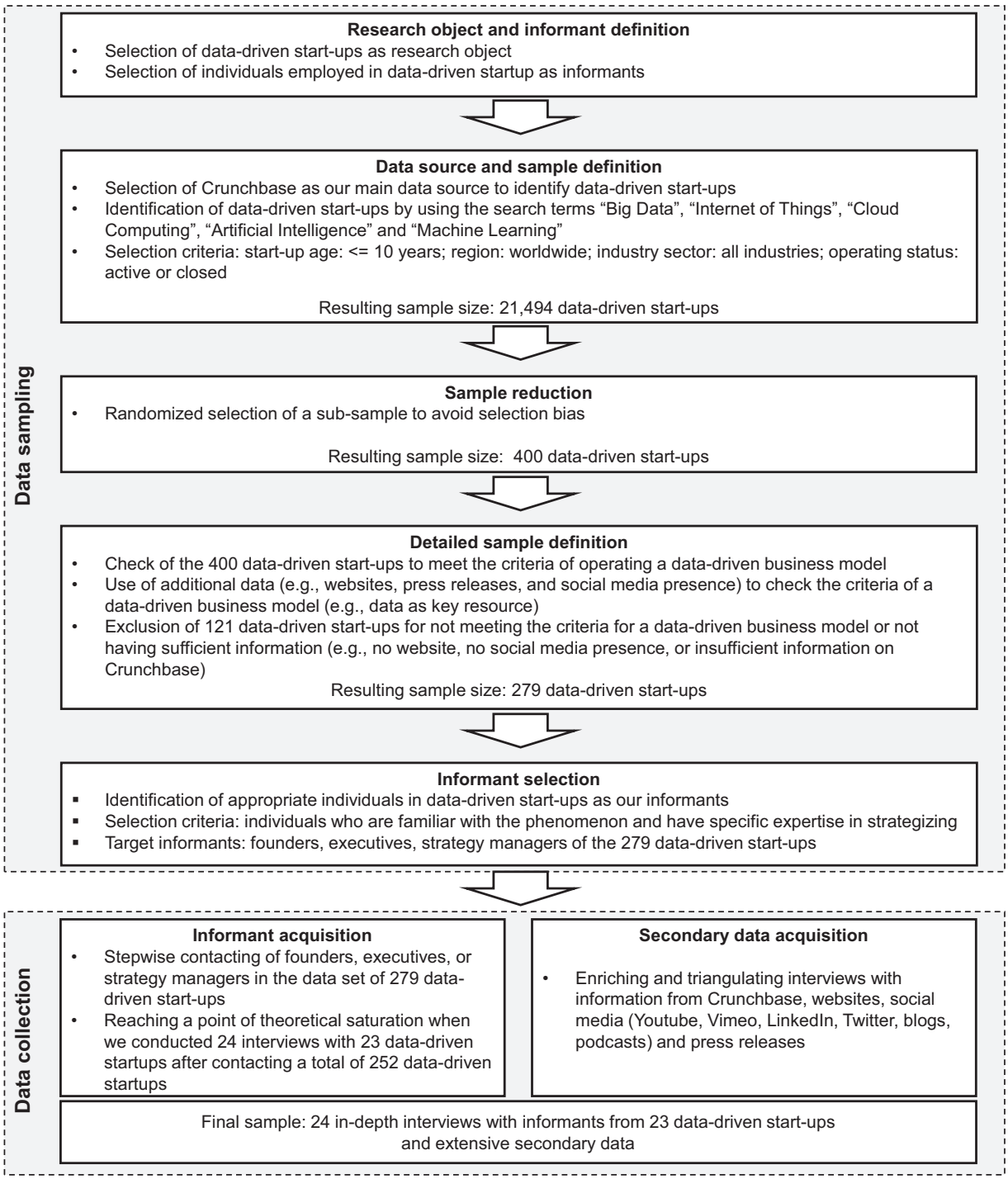

Fig. 2. Sampling and data collection procedure.

networks. Challenging extant IMP tenets on traditional start-ups, we argue that these data-driven start-ups may adopt distinct network roles and strategize differently in digitalized business networks. Grounding this argument in empirical research, we therefore employed a discovery-oriented theories-in-use approach (Zaltman, LeMasters, & Heffring, 1982; Zeithaml et al., 2020) to conduct multiple case study research on 23 data-driven start-ups (Eisenhardt & Graebner, 2007; Yin, 2018). The theories-in-use approach aims to capture the mental models of the respondents as "theory holders" that articulate how things work in a specific context at the individual level (Argyris & Schon, 1974; Zeithaml et al., 2020). Multiple case study research is particularly effective in assessing new and unexamined phenomena in practical contexts (Yin, 2018), as in our case the emergence of data-driven start-ups in digitalized business networks (Håkansson, Havila, & Pedersen, 1999). Fueling our multiple case study, the insights on the individual's thinking and acting within certain boundaries that are shaped by interactions and their contexts (Guercini & Medlin, 2020) allowed to understand how founders view their data-driven start-up's role and strategizing in digitalized business networks. Both, theories-in-use and multiple case study research are based on inductive and explorative theory building rooted in grounded theory, thereby deriving theoretical constructs from the continuous interplay between researcher and data (Glaser & Strauss, 1967). Furthermore, since we aim to identify different roles and strategizing approaches of data-driven start-ups, we needed to replicate the analysis with multiple founders and thus cases in order to build theory that is more grounded, accurate, and generalizable (Eisenhardt & Graebner, 2007; Zaltman et al., 1982).

3.2. Research setting and sampling procedure

Our units of analysis are data-driven start-ups to understand their roles and strategizing in digitalized business networks. Since responsible individuals in data-driven start-ups determine the data-driven start-ups' strategic development by their thinking and acting, they inform our study. In the selection process, we applied theoretical sampling to first identify data-driven start-ups and then recruit appropriate individuals as interviewees (Eisenhardt, 1989; Lincoln & Guba, 1985). Fig. 2 visualizes the different steps of our sampling and data collection procedure.

For the identification of data-driven start-ups, we used the Crunchbase database. Crunchbase is a platform for business information, e.g., business model, investment or funding rounds of private and public companies on a global scale (Crunchbase, 2020). The database has been increasingly applied in innovative economic and managerial research, specifically in research on start-ups (Dalle, Den Besten, & Menon, 2017). To identify suitable data-driven start-ups, we applied the search terms "Big Data", "Internet of Things", "Cloud Computing" (Chen, Mao, & Liu, 2014), "Artificial Intelligence" and "Machine Learning" (Brynjolfsson & McAfee, 2017) as they are related to digital technologies that characterize data-driven business models and thus data-driven start-ups. In addition, we only considered data-driven start-ups that were not older than 10 years to ensure that they could be considered start-ups. This threshold is widely accepted and common in both academia (Bertoni, Colombo, & Quas, 2015; Parida, Lahti, & Wincent, 2016) and practice (Kollmann, Stöckmann, Hensellek, & Kensbock, 2016). Furthermore, to increase the transferability of our findings to other contexts and thus overall generalizability, we were open to all geographical regions or industry sectors, since data-driven start-ups represent a worldwide phenomenon and are able to operate independent of their location. In addition, we followed the suggestion of Zaltman et al. (1982) to elicit ineffective and effective practitioners, i.e. we included both active and closed data-driven start-ups in our sample. This approach enabled us to paint a realistic and encompassing picture as we were interested in which network roles the data-driven start-ups and their founders failed or succeeded and why their strategizing was unsuccessful or successful. Applying the aforementioned search criteria, our data set comprised 21,494 data-driven start-ups obtained from the Crunchbase database. Building our final dataset, we then randomly drew a sub-sample of 400 data-driven start-ups. At first glance, this approach may seem counter-intuitive to the theoretical sampling procedure (Eisenhardt, 1989), however, we simply aimed to efficiently reduce our large initial sample without causing selection bias at this point. From these 400 data-driven start-ups we examined the websites, press releases, and social media presence to ensure that they met the criteria of data-driven business models as defined by Hartmann et al. (2016), e.g., if the data-driven start-up uses data as key resource for its activities. Furthermore, we excluded data-driven start-ups where we were unable to collect enough information (e.g., no website, social media presence or information on Crunchbase). This procedure led to the exclusion of 121 data-driven start-ups, resulting in our final data set comprising 279 data-driven start-ups suitable for our study.

In line with our theories-in-use approach (Zeithaml et al., 2020), we followed the principle in identifying interviewees that the data on which our study is based are best obtained from individuals who are familiar with the phenomenon (Pagani & Pardo, 2017) and have specific expertise in strategizing. Therefore, we chose to contact start-up founders, but also executives, or strategy managers as experts from the final 279 data-driven start-ups, considering that strategizing usually emanates from or is controlled by top management (Hart & Banbury, 1994).

3.3. Data collection

We contacted stepwise experts from the data set of 279 data-driven start-ups. More specifically, we sent a research participation invitation via email with an attached flyer containing rough information about the study's purpose, the interview procedure as well as the assured confidentiality. We did not share the questions with the potential respondents beforehand to avoid any biases. A reminder was sent to those who had not replied to the invitation after two weeks. Between March and November 2020, we contacted at total of 252 data-driven start-ups and eventually conducted 24 in-depth, semi-structured interviews (see Table 1) with 23 data-driven start-ups (one included a follow-up interview).

We refrained from contacting all 279 start-ups as we reached a saturation point where we found that respondents' ideas had become redundant (Zaltman et al., 1982). The number of our interviews is also in the range of typical multiple case study or theories-in-use approaches, which usually entail 15–25 participants (Griffin & Hauser, 1996; Zeithaml et al., 2020). Throughout the entire study, we use alias company names to ensure confidentiality.

Following Yin (2018), we included secondary data sources, such as information from the Crunchbase database (e.g., business model, funding rounds, latest activities), the data-driven start-ups' websites, social media websites (e.g., Youtube, Vimeo, LinkedIn, Twitter, blogs, podcasts) and 114 full-text pages of press releases designed to provide a comprehensive picture of each data-driven start-up and control for ex-post rationalization of the respondents (see Table 1). Due to this extensive data triangulation and the fact that all data-driven start-ups in our sample had only one founder in general or at least focused on strategy, we refrained from conducting interviews with different respondents of the same data-driven start-up. In this approach, we specifically followed Elfring and Hulsink (2007) that conducted multiple case study research on 32 start-ups and their respective founders with a focus on network development. For the in-depth interviews, we used a semi-structured interview guideline comprising three main topics, in line with our research questions (see Appendix A): (1) the founder's personal background and description of the business idea, business model, and main stakeholders; (2) an explanation of the initial strategy, later strategy pivots and associated trigger events; and (3) elaboration on their network role in the past, present, and future. As the empirical study progressed, the interview guide evolved and was modified accordingly following each interview's outcome. All interviews were conducted in English using a video communication tool between March

Table 1
Overview of interview partners.

#	Alias company name	Region	Interview partner	Interview duration in min	Secondary data sources[a] (no. of pages)
1	TrendTech	North America	Founder	40 + 28	Youtube, press (6), LinkedIn
2	PredictiveTech	Middle East	Founder	58	Youtube, press (10), LinkedIn
3	ComplaintPlatform	Europe	Founder	40	Youtube, press (4), LinkedIn, Twitter, Vimeo
4	SmartLock	North America	Executive	67	Youtube, press (7), LinkedIn
5	CommunicationApp*	Europe	Founder	66	Youtube, blog
6	AIPlatform	Europe	Founder	47	LinkedIn, Twitter
7	CarePlatform	Asia	Founder	56	Press (8), LinkedIn, Twitter
8	SmartImage	Europe	Founder	62	Youtube, press (3), LinkedIn, Twitter
9	MobilityApp	Europe	Founder	55	Youtube, press (2), LinkedIn, Twitter
10	GovApp	South America	Founder	65	Youtube, LinkedIn, Twitter,
11	MonitoringTech	North America	Founder	65	Press (3), LinkedIn, Twitter, blog
12	SalesTech	North America	Founder	34	LinkedIn, Twitter, podcast
13	SearchTech	Europe	Founder	50	Youtube, press (10), LinkedIn, Twitter, blog
14	RoboTech	Europe	Founder	58	Youtube, press (7), LinkedIn
15	MRPPlatform	North America	Executive	60	Press (7), LinkedIn, podcast
16	FinApp*	North America	Founder	58	Twitter
17	FinancialPlatform	Asia	Founder	61	LinkedIn, Twitter
18	SpeechAIPlatform	Europe	Founder	68	Youtube, press (15), LinkedIn, Twitter
19	CloudTech	North America	Founder	72	Youtube, press (4)
20	MarketingTech	Europe	Founder	75	Press (3), LinkedIn, blog
21	PsychologyTech	North America	Founder	46	Youtube, press (13), LinkedIn, Twitter, podcast
22	AnalyticsTech	Europe	Manager	40	Youtube, press (8), LinkedIn, Twitter, Vimeo
23	GiftPlatform*	Europe	Founder	73	Youtube, press (4), podcast

[a] Note: Crunchbase and homepage were always included in the analysis for each data-driven start-up.
* Closed data-driven start-up.

and November 2020, with the exception of two interviews that were conducted in German. The interviews lasted 56 min each on average and were recorded and transcribed verbatim, comprising 429 full-text, transcribed pages.

3.4. Analysis and interpretation

We employed the three-step procedure developed by Gioia, Corley, and Hamilton (2013) to progress systematically and with qualitative rigor from raw data to our theoretical constructs (see Fig. 3). MAXQDA software served as our main tool to document the analysis, yielding overall 1860 codings.

First, open and inductive coding was conducted by three members of the research team who read the transcribed interviews and secondary data simultaneously without using a predetermined coding scheme. In this way, so-called in vivo codes were created that contain words or statements that are noteworthy and relevant to our research questions (Corbin & Strauss, 2008). Specifically, in this step, we captured each founder's theories-in-use to understand how they perceive, interpret, and construct meaning for the network roles of their data-driven start-up while strategizing in digitalized business networks. We coded every interview immediately after conducting it and discussed the in-vivo codes constantly throughout this first analysis step until consensus was reached. In the end, we elaborated first-order concepts that emerged from the founders' theories-in-use and thus from the data itself. In this context, we emphasize that we derive our insights specifically taking the perspective of the founders and triangulating it with our secondary data, making it clear from which point of view we approach our research questions (Guercini & Medlin, 2020).

Second, we used the ARA model from IMP literature (Håkansson & Snehota, 1995), which has been proven to be a valid concept for business network analysis in the digital context (Pagani & Pardo, 2017). We combined it with the framework and its components on data-driven business models from DDBM literature to structure our in-vivo codings, thereby describing each data-driven start-up's activities, resources, and actors. Building on this basic structure of each data-driven start-up, we aimed to get a clear understanding of the data-driven start-up's relations to other actors within the digitalized business network. This procedure enabled us to determine the network position and network ties to access data. Moreover, we included additional actors such as competitors and collaboration partners to illustrate the individual network of each data-driven start-up. In order to grasp the data-driven start-up's dynamic strategizing, we then investigated how the data-driven start-ups evolved from their initial business ideas to current or planned status by mapping the chronological sequence of strategic milestones (see example in Appendix B). Such strategic milestones included changes in key customers, data sources, or key activities of the data-driven start-up's business model. For each case, we compared the network constellations and plots, and discussed similarities and differences to reach a shared understanding of each data-driven start-up's

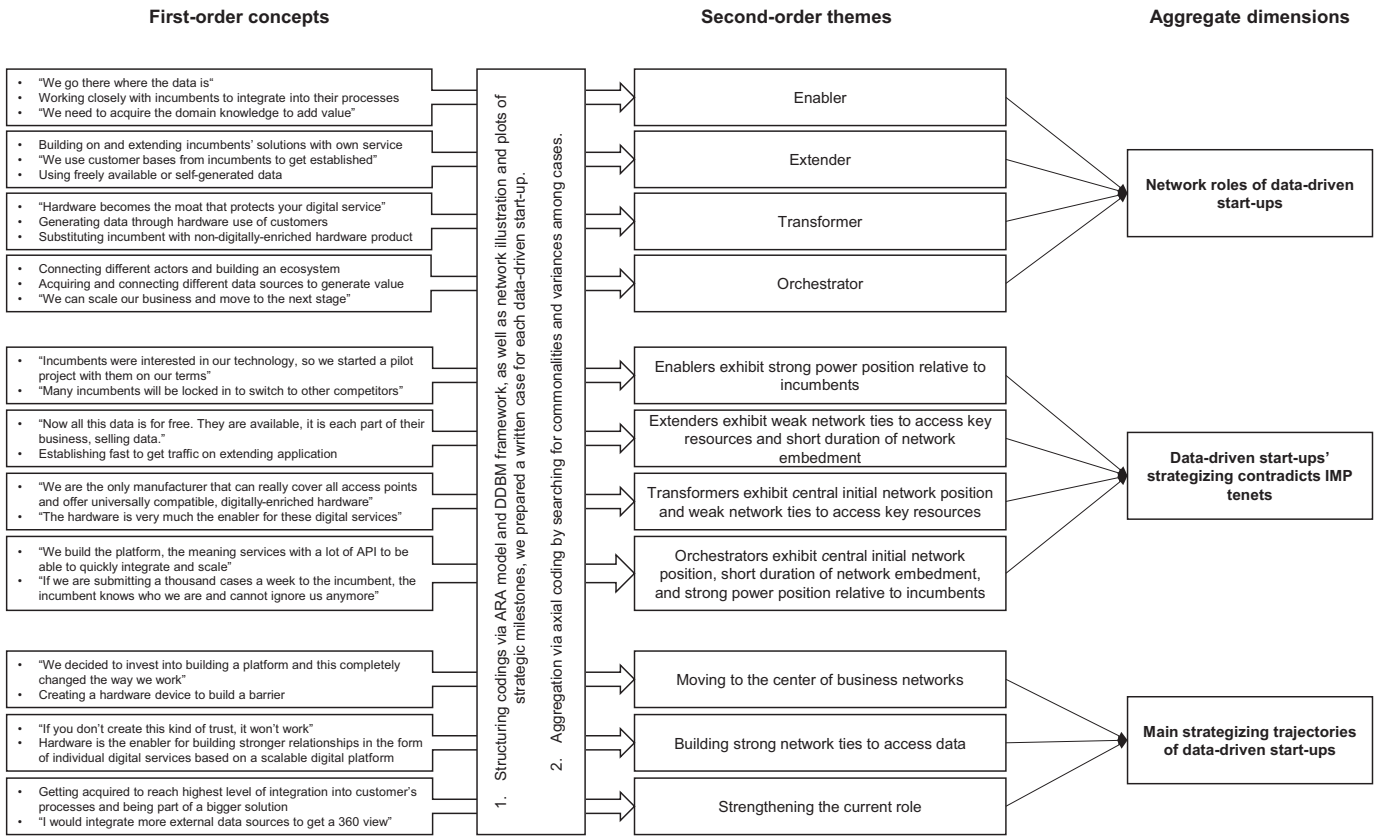

Fig. 3. Data analysis structure.

network positions and strategizing activities. Taking all relevant information into account, we then prepared a written case for each data-driven start-up to formulate an individual way of strategizing, resulting in a total length of 53 full-text pages across all 23 cases (each case description is available from the authors on request). Ultimately, we built on this to create second-order themes by searching for commonalities and variances in our structured in-vivo codings and across the 23 cases through axial coding, thus mirroring the raw data through the researchers' interpretation.

Third, we further theoretically abstracted from our second-order themes to elaborate distilled dimensions.

Following the suggestion of Lindgreen, Di Benedetto, and Beverland (2020), we have moved the section on how we ensured rigor and robustness of our study results to Appendix C for saving page space.

4. Results

Based on our empirical analysis, we derived four distinct network roles and different strategizing approaches. First (4.1), we describe each network role. Second (4.2), we demonstrate to what extent strategizing in the four network roles of data-driven start-ups differ from IMP literature's strategizing tenets. Third (4.3), we describe strategizing trajectories by examining typical paths between these network roles.

4.1. Data-driven start-ups' roles in digitalized business networks

In the continuous interplay between our inductive case analysis and the corresponding theories from IMP and DDBM literature, we identify and describe the network roles of data-driven start-ups by taking the founder's perspective. Thereby, it became particularly evident that these network roles differ distinctly in the strength of ties to access their data as key resource and the centrality of their network position. In other words, data-driven start-ups' varying network roles distinguish themselves in terms of (1) how strong the network ties need to be to gain access to data as a key resource and (2) where the data-driven start-ups are positioned in relation to other actors within the digitalized business network. We operationalize the strength of network ties to access data by determining how costly the data acquisition is (e.g., close collaboration for access to data versus open data access or data self-generation). In terms of network position, we assess the number of ties to other actors in the network (e.g., customers, partners, suppliers) and specifically analyze whether the value proposition in the data-driven business model represents a separate offering (e.g., stand-alone offering vs. offering that builds on and/or depends on other actors). Thereby, the different dimensions (weak vs. strong connections to data access; peripheral vs. central network position) should be viewed as a continuum rather than strict either/or categories with clear thresholds. Nevertheless, we created a four-field matrix that serves as a classification framework for the identified network roles to provide a straightforward and simplified tool to analyze data-driven start-ups and their network roles for IMP research. The reasoning of the continuum can be illustrated, for example, by showing that data-driven start-ups within the same quadrant are more aligned with a particular network role than others. Furthermore, our classification framework acts as structural guidance for the following role description, starting with the *enabler* and continuing counterclockwise (see Fig. 4). In our description, we assigned the data-driven business model's components "key activity", "offering", "revenue model", and "cost structure" to the ARA model's activity, "key resource" to resource, and "customer segment" to actor. The combined use of the ARA framework (italic heading) and data-driven business model components (italic term in text) enabled a rich and structured description of the four network roles for data-driven start-ups. Due to space limitations, we have moved the overview of our extensive analysis to Appendix D.

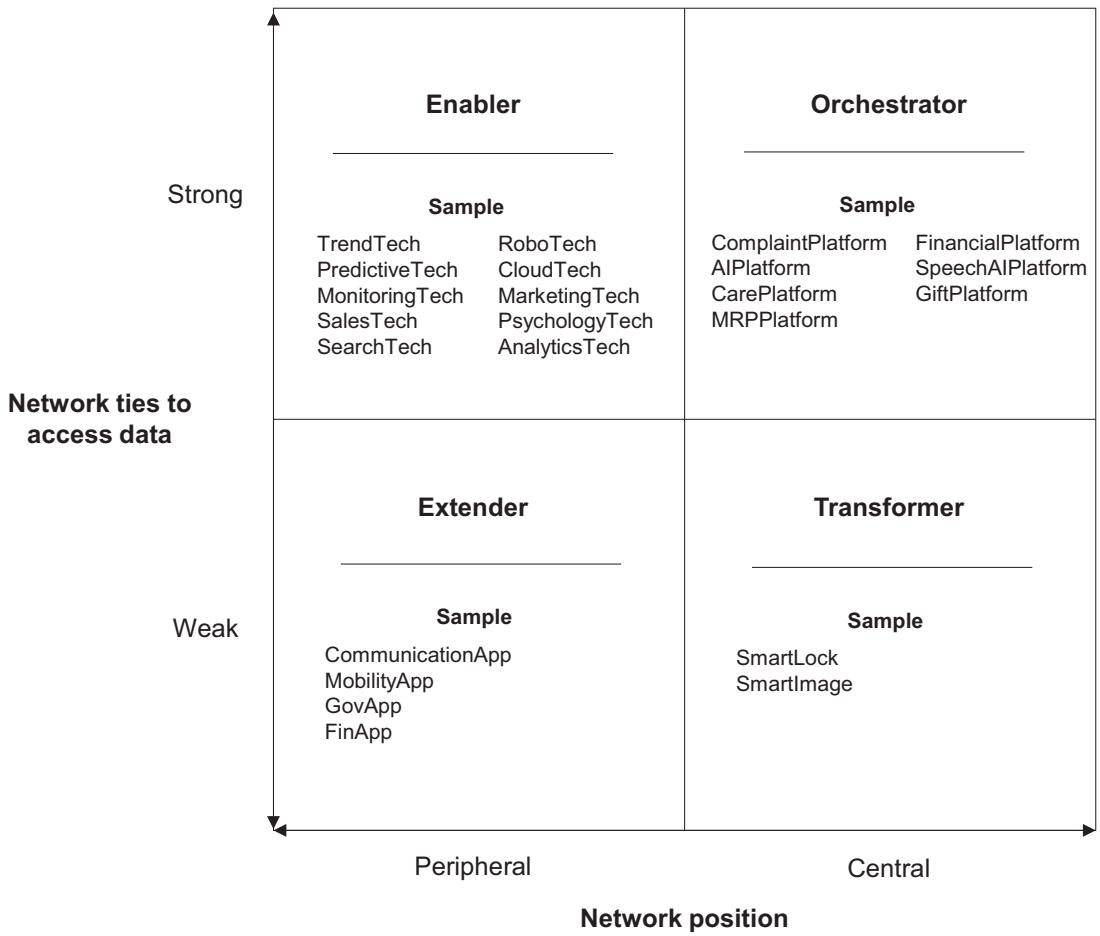

Fig. 4. Classification framework of data-driven start-ups' identified roles in digitalized business networks.

4.1.1. Enabler

4.1.1.1. Activities. Data-driven start-ups in the network role of enabler operate data-driven business models that provide incumbents with the data-driven capabilities needed to meet current and new customers' demands. For example, the *offering* of PredictiveTech is a predictive maintenance service to incumbents in the process industry, helping them to ensure a high level of machine availability and thus a high and steady product flow. Thereby, the *key activity* of enablers usually focuses on the processing, analysis, or visualization of data. RoboTech, for instance, has developed a retrofit kit to process, analyze, and feed data from customer rule-based programmed robot systems back into the robot, making them smarter, i.e., ready for human-machine collaboration or more autonomous operations. Enablers typically base their data-driven business models on subscription-based *revenue models* to establish a regular and steady source of income. SalesTech, for example, relies on a Software-as-a-Service model with a monthly subscription fee. Due to the fact that enablers depend on external data and domain knowledge that is complex to acquire and not freely accessible, they exhibit a rather disadvantageous *cost structure*. For instance, the predictive maintenance solution of PredictiveTech is not transferable to other industries or even factories, resulting in slow and costly growth.

4.1.1.2. Resources. To gain access to the *key resource* in the form of data, enablers rely on trusting relationships with their customers or data suppliers, ultimately leading to a high dependence on customer-owned data sources that are not freely available. For instance, SalesTech specifically relies on point-of-sale data providers to make recommendations to restaurants based on complex best-in-class benchmarking to increase sales and profits. However, besides data as key resource, enablers often rely on domain knowledge to understand the customer and add significant value at the customer end, which often requires cooperations with third-parties. As a concrete example TrendTech provides trend analysis to incumbent fashion brands. It works closely with market research agencies to benefit from their existing client portfolio, customer channels, and deep knowledge of clients' market research processes so that they can successfully market their own offering. The agencies also benefit from this partnership as they can complement their existing market research services with new data-driven offerings.

4.1.1.3. Actors. Enablers often explicitly target incumbent industries or niches that already have big data sets, as well as the need to extract valuable information from them. As a result, enablers' key *customer segments* are in B2B industries, which are able to provide such large data sets. In our cases, the B2B customer segments range from fashion to process industries, logistics, and pharmaceuticals.

Overall, enablers rely on strong ties to gain access to the data they need, making it costly to deploy their offerings and thus grow at scale. In addition, enablers have few but selected ties to customers, suppliers, or partners. With their offerings, they do not aim to replace incumbents and their products, but to help them succeed with their data-driven knowledge in digitalized business networks. They are therefore located in peripheral network positions.

4.1.2. Extender

4.1.2.1. Activities. The data-driven start-ups assigned to the extender role exhibit *offerings* that build on existing data-driven solutions from

other actors (often operating systems or digital platforms) and extend them. For example, CommunicationApp builds on a widely used email software to provide an email automation service that, among other things, automatically assigns emails to associated projects. The *key activities* of extenders include particularly the data generation or acquisition and its analysis. For instance, GovApp extends incumbent policy advisory services by searching freely available legislative texts to assess their impact on specific industries (e.g., new laws on product testing in pharmaceutical or beauty), and then ultimately sells this information to the respective incumbents. With regard to the *revenue model*, we observe that extenders mainly use a freemium model to generate income. For example, CommunicationApp offers the basic features of its email automation service for free, while the full feature set can only be used if the end-user pays a monthly subscription fee. However, there are also variants in which only certain customer segments are charged. FinApp, for example, which extends existing banking applications by bringing them together, offers its application free of charge to individual end-users, while selling usage data to various banking institutions and thereby providing them with a comprehensive overview of their customers' financials. The *cost structure* has a fairly high specific cost advantage because access to the data is inexpensive or even for free. By offering their own application to an existing large community provided by the incumbents they are adding to, extenders also save on marketing costs and can scale quickly.

4.1.2.2. Resources. A key differentiating factor of extenders is that their data-driven business models rely on freely available data and/or the usage data of a high number of end-users as *key resources*. MobilityApp, for instance, extends existing routing service applications by integrating freely available social media data regarding disruptions in public transportation systems. In addition, extenders ensure that they offer platform-agnostic services to avoid dependence on incumbents' applications upon which they are based. As an example, MobilityApp offers its application independently of the routing service application or mobile operating system used.

4.1.2.3. Actors. Since extenders rely on the incumbents' application, they address the incumbents' usually large B2C user base as their main *customer segment*. However, using GovApp as an example, we see that extenders are also offering their data-driven business models in the B2B space.

In sum, extenders exhibit weak network ties to access data, since they focus on freely available data via open APIs or generate their data through the customer's usage. Such characteristic enables them to scale quickly and focus on data management instead of data acquisition. In addition, although extenders usually address a large number of potential end users, they tend to be located on the periphery. This is due to the fact that they are not able to provide their offering on their own, but must always build on existing established solutions positioned at the center of digitalized business networks.

4.1.3. Transformer

4.1.3.1. Activities. The data-driven start-ups assigned to the transformer role provide *offerings* that transform incumbents' (mostly non-data-driven) product and service business networks by enriching them with digital components. SmartLock, for example, offers a physical door lock with IoT connectivity features to small and medium sized companies that provides easy and seamless access for authorized individuals using their smartphones. The *key activity* of transformers generally constitutes generating the data by tracking its users' data and analyzing it to provide complementary data-driven services. Moreover, SmartImage, for example, connects the various users of its smart picture frames via an integrated messenger plug-in, ultimately building a social network. The *revenue model* of transformers is typically based on a one-time sales component and a regular subscription-based fee for additional data-driven services. SmartImage, for instance, charges the physical device only once for a relatively high price and a small monthly fee for the connectivity feature. The *cost structure* of transformers is rather advantageous in two respects. First, because the required data is obtained via their own physical device, the data acquisition costs are marginal. Second, due to the outsourced production of their physical device, transformers benefit from economies of scale of their large suppliers.

4.1.3.2. Resources. The access to the *key resource* in the form of data is usually ensured via the physical device that collects the users' data and enables subsequent analysis, resulting in the development of further services (e.g., monitoring office capacity or employee movement habits as in the case of SmartLock). To be successful, transformers therefore need significant physical product expertise in addition to digital capabilities for data analysis. For instance, SmartImage that offers a smart picture frame to elderly people decided to develop their own smart and connected device when they realized that existing solutions were not meeting their expectations. However, the production of the physical device is usually outsourced to large contract suppliers. As a result, trusting relationships are required to manufacture the physical device rather than to access the data.

4.1.3.3. Actors. Transformers target the *customer segments* of incumbents by offering a directly competitive product. These customer groups can be B2C (e.g. as with SmartImage) or B2B customer segments (e.g. as with SmartLock).

In total, transformers exhibit rather weak ties necessary to access the required data, as they collect user data via the physical device installed at the customer side. Due to the competing offering and resulting replacement of the incumbents' usually non-data-driven products, transformers are inherently located in the center of digitalized business networks.

4.1.4. Orchestrator

4.1.4.1. Activities. Data-driven start-ups in the orchestrator role create *offerings* by indirectly connecting several other actors, often via digital platforms. FinancialPlatform, for example, brings together individual borrowers and lenders on a digital platform, creating easy access to capital for borrowers on the one hand and an opportunity for lenders to make profits on the other. The *key activities* are usually the aggregation, processing and analysis of data obtained through mediation and exchange between many different actors that were not necessarily linked before. A further example in this regard is MRPPlatform, which provides a SaaS manufacturing resource planning (MRP) solution for small and medium-sized manufacturing companies, thereby connecting different suppliers and original equipment manufacturers (OEMs). By using the digital platform within the individual company, data is collected and processed about their production capacities, which in turn is made available to all platform actors, thus improving the production utilization of the single company. The *revenue model* typically aims to charge only one actor group using the platform. For example, since ComplaintPlatform does not provide legal assistance, but simply seeks to collect and analyze the data on the many different complaint cases across different companies, it offers the data-driven service free of charge to individual persons with complaints and charges the incumbents for the aggregated complaint reports. Thereby, the revenue model of orchestrators is often transaction-based, i.e., the paying actor group pays only for the actual transaction. Despite the fact that strong ties are necessary to access the data of the individual customer, orchestrators are characterized by a *cost structure* that is aligned to enable a high scalability potential. For instance, once a critical user base is achieved, the network effects help MRPPlatform to acquire additional data through every single transaction at marginal costs. Therefore, the

specific cost advantage is rather high for orchestrators.

4.1.4.2. Resources. Orchestrators build their data-driven business models primarily on proprietary data as *key resource*, which requires them to establish strong relationships with their customers and data providers to gain access to it. For instance, potential borrowers must provide detailed data about their personal and financial situation, which is then automatically collected via an application on the borrowers' respective smartphone to measure the probability of default. In many cases like this, non-proprietary data is also included, such as freely available information from social media, to triangulate the data obtained from the smartphone.

4.1.4.3. Actors. Orchestrators rely on a large user base, as individual users will only participate if there is a large enough set of other users from which they can benefit through exchange. The *customer segment* can be either B2B or B2C. ComplaintPlatform serves as an example. It indirectly connects individual complainants, e.g., regarding a flight delay, and the respective complaint initiator, e.g., an airline, by aggregating all complaint issues and then directly addressing the complaint initiator in a bundled form, making it impossible for the latter to ignore the complaints. The more users the platform has for its complaints, the stronger and thus more successful it becomes against the incumbents causing the complaints, which in turn attracts more additional users. These so-called network effects can only be generated if the orchestrators are positioned at the end-user interface between individuals and companies, where the actual exchange between the two actors takes place.

In summary, orchestrators require strong ties and substantial investments to gain access to the necessary data and eventually establish themselves at the end-user interface. However, after reaching a critical mass, orchestrators are able to grow at scale and marginal costs by exploiting network effects, thereby continuously attracting additional users and building a large customer base. Therefore, orchestrators are at the center of digitalized business networks, often transforming existing ties of incumbent actors.

4.2. Analyzing data-driven start-ups' network roles in the context of strategizing contradictions

Based on the rich description of data-driven start-ups' network roles, we demonstrate how our sample firms strategize in the four network roles against the contradictions that we identified and illustrated in the theoretical background (see Fig. 1 in Chapter 2). These four contradictions refer to the *initial network position* (peripheral vs. central), *ties to access key resources* (strong vs. weak), *duration of network embedment* (long vs. short), and *power position relative to incumbents* (weak vs. strong). Table 2 illustrates how each network role either confirms the IMP strategizing tenets or contradicts them, thereby confirming the DDBM strategizing tenets.

Table 2
Network roles in the context of strategizing contradictions between IMP and DDBM literature.

	Network role			
Contradiction	Enabler	Extender	Transformer	Orchestrator
1. Initial network position	Peripheral	Peripheral	**Central**	**Central**
2. Network ties to access key resources	Strong	**Weak**	**Weak**	Strong
3. Duration of network embedment	Long	**Short**	Long	**Short**
4. Power position relative to incumbents	**Strong**	Weak	Weak	**Strong**
Number of confirmed DDBM tenets	1/4	2/4	2/4	3/4

Notes: Confirmed DDBM tenets are indicated in bold

4.2.1. Network roles in the context of contradiction 1 related to initial network position

Contradiction 1 refers to the fact that (data-driven) start-ups enter pre-existing business network structures in a rather peripheral (IMP tenet) or central (DDBM tenet) network position. For *enablers*, the IMP tenet holds true because they operate in peripheral network positions, adjusting and customizing their offerings to the individual customer that is located centrally in the business network. This approach leads to only a small number of ties with other actors in the business network. Also, the *extenders'* strategizing fulfills the IMP tenet, as they are positioned on the business network's periphery. With their data-driven offerings, extenders dock onto incumbents' digital solutions like large operating systems (OS) that have established themselves over a long time period at the center of an often digitally mature network.

> "We are not really reinventing the e-mail because we are still based on Office 365, […] so we have APIs etcetera. We are not doing our own e-mail client, we are just adding some features." (Founder, CommunicationApp).

However, *transformers* tend to confirm the DDBM tenet, as they usually start in central network positions in smaller niche markets that are not served by incumbents to avoid strong competition from the beginning. If the establishment of the central position in these niche markets is particularly successful, transformers may further increase the number of ties and move toward bigger customer segments, where they can replace the incumbent in bigger sub-markets or even the whole market. In the long run, transformers aim to replace offerings from centrally positioned incumbents.

> "First, our customers were technology start-ups and then […] gyms, co-working spaces, we have a lot of real estate agents. […] And now we're pretty firmly in that 15 to 500 people office segment." (Executive, SmartLock).

Similar to transformers, *orchestrators* confirm the DDBM tenet, as they operate in central network positions. They are inherently designed to act as central nodes or intermediaries between many different actors in a business network. This includes viewing the business network as an (eco)system from the very beginning.

> "So to be able to perform what we do, we needed to connect to other systems in the hospital. So […] we built the platform […] with a lot of APIs to be able to quickly integrate with different hospital systems. So ecosystem was in the core of the design of the system." (Founder, CarePlatform).

4.2.2. Network roles in the context of contradiction 2 related to network ties to access key resources

Contradiction 2 refers to the fact that data-driven start-ups need strong (IMP tenet) or weak (DDBM tenet) network ties to access data as their key resources. For *enablers*, the IMP tenet pertains, as they heavily depend on customers' proprietary data as a key resource. Therefore, they need to apply certain strategic measures to access and leverage these data. Moreover, enablers often need to acquire specific domain knowledge in the customer sector and combine it with their digital capabilities to reach a solution to add value at the customer end. This knowledge also includes expertise on how to meet incumbent customers where they are. This is necessary because enablers often offer data-driven business models that incorporate novel digital technologies, which could make incumbent customers reluctant to adopt and integrate them into their internal processes. As a result, enablers often require collaborations with third-party incumbent knowledge and technology providers (e.g., agencies) that already are established in the customer's business

networks, thereby approaching incumbent customers through channels familiar to them.

> "So we decided to meet them halfway, rather than forcing them to learn [our digital service] before they are ready. […] So as close as we can fit it in their existing routine the better we are going to be off so that led us acting a little bit more like agencies and even kind of collaborating with existing agencies to be able to help them make the switch." (Founder, TrendTech).

However, *extenders* and *transformers* confirm the DDBM tenet, as they can access data largely independently of other actors. Thus, both network roles do not need to build strong ties with other actors to get the necessary data for their offerings. Specifically, extenders and transformers process freely available data, e.g., from social media or operating system platforms that are involved in rather weak ties. Alternatively, they generate the necessary data via their own application or hardware component, making them fully independent from external data providers. This data self-generation also includes the characteristic of being platform- or hardware-independent, potentially serving a large circle of potential users and avoiding the creation of new dependencies.

> "For us, the hardware is very much the enabler for these software services. The basic principle was the way we have set it up now, we have the hardware that is universally compatible. We think we are the only manufacturer that can really cover all access points." (Executive, SmartLock).

For *orchestrators*, the IMP tenet holds true, as they need to access data from multiple actors and often proprietary data sources in the business network. Therefore, to maintain the ability to scale, orchestrators focus on not being perceived as a threat by data-supplying actors within the business network to build trust with many different actors and, consequently, gain data access.

> "So where there were existing players in the market, it was basically not to become a threat to them because then you could blow up. If they would go 'okay, they are not trying to threaten us', […] you get this positive reinforcement in the market rather than people seeing you as a threat and therefore saying, 'oh yeah, you shouldn't trust those guys' […]. So it allows us to build up a position of trust within the market place." (Founder, ComplaintPlatform).

4.2.3. Network roles in the context of the contradiction 3 related to the duration of network embedment

Contradiction 3 relates to whether start-ups take a long (IMP tenet) or short (DDBM tenet) time to become embedded in a business network. *Enablers* fulfill this IMP tenet, as they exhibit rather low growth rates and limited scalability, as the industry- or even plant-specific data-driven offering cannot be transferred to other applications easily. As an enabler, understanding the customer's problems and embedding a suitable solution into the customer's processes are a tedious procedure, given that each customer is unique in its characteristics.

> "The knowledge and the data by the way is worth nothing outside the context of the specific plant. […] Even to create the machine learning model in one plant and use it for another plant, it can't work. […] You can learn from this specific plant only for this specific plant." (Founder, PredictiveTech).

By comparison, *extenders* confirm the DDBM tenet because they can grow at fast scale. They profit from the incumbent OS provider's high customer reach and growth rate: therefore, extenders grow rapidly, as they use the incumbent's existing user base. For *transformers*, the IMP tenet applies, as the scaling depends on the efficiency of their hardware management in terms of development, logistics, and (external) production. Often, hardware management is inefficient, hindering the business model's scaling and, consequently, the pace of business network establishment.

> "[Only software] is much easier because you can stay in your room and just work and you don't have to manage any hardware, which is a lot of work in terms of logistics." (Founder, SmartImage).

Orchestrators, in turn, confirm the DDBM tenet, as they can embed themselves quickly after they have established resource access. Due to their intermediary function, they play a key role, as orchestrators reduce complexity, thereby contributing to the rapid development of digitalized business networks, and if the necessary capital is available, establishment in digitalized business networks is possible in a short period of time.

> "You don't have that [long duration], but you need to have money […] and then you can be really, really fast." (Founder, GiftPlatform).

4.2.4. Network roles in the context of the Contradiction 4 related to the power position relative to incumbents

Contradiction 4 refers to the fact that start-ups are in a weak (IMP tenet) or strong (DDBM tenet) power position relative to the incumbent. *Enablers* confirm the DDBM tenet as they often possess specific data-driven knowledge in certain industries or domains, which can become a valuable asset to gain power. After all, incumbent customers often lack the digital knowledge and skills for data analytics, relying on enablers to leverage their existing data sets. Therefore, established actors often actively approach suitable enablers for collaborations by setting up customized start-up events or specific incubator programs and providing their data based on their own motivation and problem definition.

> "And what happened to us in the next base is that then a [big incumbent], they did scouting for a technology because they understood at that point the concept of Industry 4.0 […], so they started to look for technologies and they selected our technology for a pilot." (Founder, PredictiveTech).

However, for *extenders*, this IMP tenet applies. While they can align their data-driven offerings with competing OS providers, they must adapt to their governance policies or even can be dependent on their willingness to let the data-driven start-up participate.

> "Of course, on the commercial side we approached [the OS provider] to see if they could help us to advertise our product through their sales. In fact, they may do it but first for bigger players and then for players targeting a specific sector like us." (Founder, CommunicationApp).

Likewise, *transformers* confirm the IMP tenet because they (at least initially) are usually too small and insignificant in digitalized business networks, especially if they operate in niche markets. This approach may lead to a weak power position vis-à-vis incumbents.

However, *orchestrators* demonstrate confirmation of the DDBM tenet, as they can act as centrally positioned disruptors of an entire business network, altering established power structures once access to customer data via strong ties is established and many different actors are connected in a new way. The dominant and, thus, powerful business network position is particularly possible to achieve because their main focus is to use the central network position and the absence of physical resources to scale rapidly in user numbers through (direct and indirect) network effects.

> "I think we are a disruptor and we are really changing the way how basic services are done, […] so we do not really need to meet the customer in person, we just need to do a biometric scan […]. So, we would classify ourselves as a disruptor and our focus is to grow into not just a disruptor but the primary institution driving financial inclusion." (Founder, FinancialPlatform).

In summary, out of the four DDBM tenets, *enablers* exhibit only one

and, thus, pursue similar strategizing approaches compared with those of traditional start-ups. *Extenders* and *transformers* fulfill two of the proposed DDBM tenets. *Orchestrators* demonstrate three DDBM strategizing tenets, i.e., data-driven start-ups in this network role are particularly tailored to match the characteristics of strategizing in digitalized business networks. As a result, orchestrators may have the highest probability of being able to drive other players in digitalized business networks to their advantage, rather than being driven by them, leading to high disruption potential overall. In this context, we emphasize that we observed varying nuances in how strongly the IMP tenets have been contradicted by the individual data-driven start-ups in their respective network roles. For illustration, we take the enabler TrendTech that integrates its fashion trend analysis solution into the offerings of incumbent market research agencies. However, despite cooperating with such agencies, TrendTech is able to absorb budget share that is normally spent by the customer (e.g., incumbent fashion companies) on traditional, non-data-driven market research offerings. As a result, TrendTech may increasingly substitute the offerings of incumbent market research agencies in the long term, after initially supporting them and strengthening their network position. This may ultimately lead to a shift toward a more central network position, such as the role of a transformer. Consequently, data-driven start-ups gradually may change their network role over time to move into the network role that best suits them in digitalized business networks.

4.3. Strategizing trajectories between data-driven start-ups' different network roles

Based on our analysis related to the drawn time sequence of different data-driven start-ups' strategy milestones, i.e., changes in data-driven business model components, we can derive three main strategy trajectories, each with two sub-trajectories. Moreover, we identify an additional strategizing trajectory that is associated with failure. We visualize all strategizing trajectories based on our classification matrix (see Fig. 5). The role adjustment usually results in either a change in network position (A) or in the strength of ties to access data (B). In addition, we find that particularly data-driven start-ups in the roles of enablers and orchestrators continue to focus on strengthening them (C). However, the simultaneous change in tie strength and network position may increase the probability of failure (D).

In this regard, we highlight that these strategizing trajectories are typically not linear or unidirectional. To the contrary, strategizing constitutes a highly iterative and non-linear process, shading the picture of dynamics in digitalized business networks in various colors. The more rigorously the data-driven business model has been designed and implemented, i.e., which strategic milestones have been undertaken and in what order, the more straight forward the strategizing trajectory will unfold. For instance, CloudTech initially offered a public stand-alone cloud solution in the B2C market focused on convenient data storage of photos and videos, aiming to connect different actors (sharing of photos between individuals) on a digital platform in the network role of an orchestrator. However, the founder soon realized that the willingness to pay for such solutions in the B2C market was quite low. Therefore, the founder decided to adapt the data-driven business model and focus on the B2B market instead by cooperating with hard drive manufacturers and integrating a highly secure private cloud solution into their products. This move changed not only the customer segment and offering, but also the key activities (e.g., from data storing to data processing) and transformed CloudTech into the enabler it is today. The founder then monetized this successful move by selling the company to an incumbent data security firm, thereby further strengthening the role as an enabler. Therefore, we argue that in a few cases, in addition to the main strategizing trajectories we identified, there are alternative dynamic strategy paths that even move in the opposite direction between the different network roles, but only as part of an iterative process before the founders then follow the paths we identified. The distribution of our sample across the different trajectories is shown in Table 3.

4.3.1. Moving to the center: "Taking the reins in hand"

The majority of our data-driven start-ups started in a peripheral

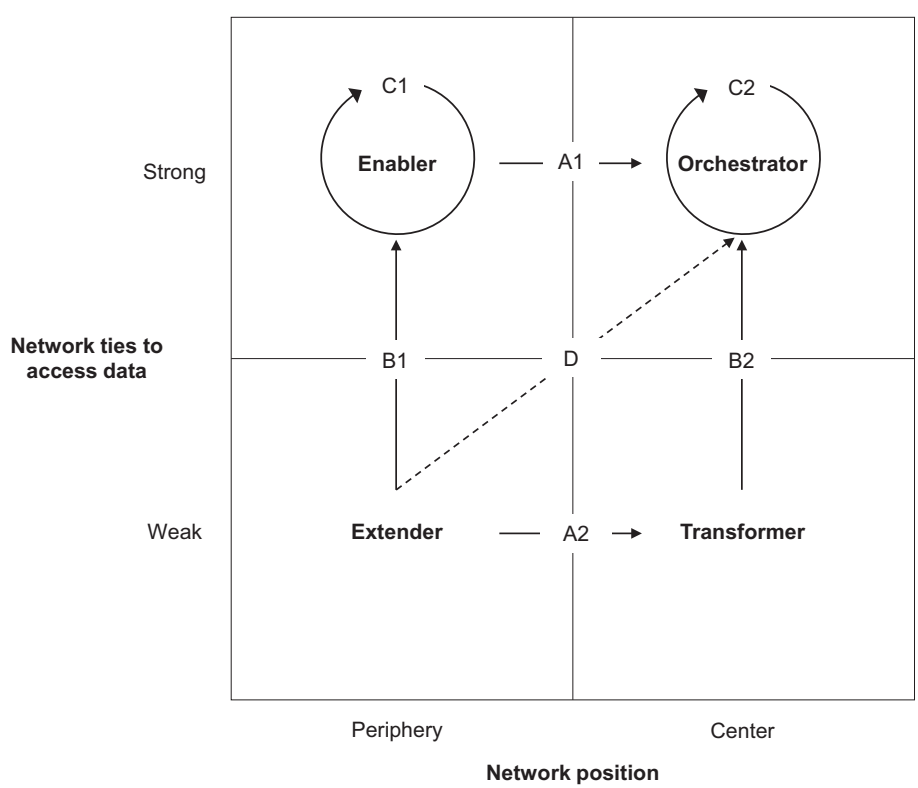

Fig. 5. Strategizing data-driven start-ups' trajectories in digitalized business networks.

Table 3
Distribution of sample firms across strategizing trajectories.

Strategizing trajectory	Number of sample firms	Sample firm
(A1) Enabler to Orchestrator	11	CarePlatform, MRPPlatform, FinancialPlatform, SpeechAIPlatform, TrendTech, AIPlatform, SalesTech, SearchTech, RoboTech, MarketingTech, AnalyticsTech
(A2) Extender to Transformer	1	SmartImage
(B1) Extender to Enabler	3	MobilityApp, GovApp, MonitoringApp
(B2) Transformer to Orchestrator	1	Nexkey
(C1) Enabler to Enabler	2	PredictiveTech, PsychologyTech
(C2) Orchestrator to Orchestrator	2	ComplaintPlatform, GiftPlatform*
(D) Extender to Orchestrator	2	CommunicationApp*, FinApp*
Other: Orchestrator to Enabler	1	CloudTech

*Closed

position, i.e., in the role of enabler or extender. But, over time, the founders aimed to move toward the center to reach an increased customer amount, extend their business, and achieve a more powerful position in the digitalized business network. To put it bluntly, they aimed to take the reins of the ties in the digitalized business network in hand. In particular, *enablers* often pivot from a consulting-oriented and customized data-driven business model to the more scalable and modularized offering of an orchestrator, becoming better able to exploit data's characteristics in terms of fast and perfect replication with marginal costs close to zero, supporting strategizing in digitalized business networks (A1). With the consulting model of close and trusting ties, the enabler role is only a means to an end to learn from few initial data-providing customers, in which their own offering can add the best value, ultimately gaining an understanding of how digitalized business networks function. The move toward the orchestrator role often is related with large investments in scalable infrastructure and additional development resources. Acquisition of necessary financial resources often is associated with fewer hurdles than in other network roles, as venture capital investors view data-driven start-ups with high scaling and, thus, value enhancement potential to as being particularly attractive.

> "And then we decided to invest into building a platform. And so this completely changed the way we worked. […] It was a very heavy investment […] With the consulting model we could learn […]. For customers I think this consulting model built strong relationships, we were very close with our clients, but the goal is now to scale our solution. This is like a very precise goal, […] to get some funding to grow the company." (Founder, AIPlatform).

In the role of an *extender*, the data-driven start-ups' founders may aim to differentiate themselves from competitors by moving toward the center into the role of transformer, thereby including a hardware component that complements the existing add-on application (A2). Specifically, the implementation of complex hardware components can serve as strong protection against new actor entry and imitation, which may provide a greater competitive advantage and, thus, more consistent establishment in business networks.

> "So, on the other hand it is like a barrier […], because someone who is working only on software, usually they don't know the hardware. […] So, we had to create a device." (Founder, SmartImage).

4.3.2. *Building strong network ties to access data: "Getting the candies you desire"*

Data-driven start-ups in the role of extenders and transformers exhibit both weak ties to access necessary data. To reinforce their position in the business network, they aim to increase their ties' strength to actors that can provide proprietary data. To use an analogy, it is about "getting the candies you desire", considering that proprietary data often mean competitive advantage. Particularly, *extenders* may include customer or third-party data that are not freely accessible or self-producible to shift to the role of an enabler (B1), while still remaining in a peripheral network position. Close and trusting ties with data providers can serve as protection against imitating actors, thereby stabilizing the network position at the periphery.

> "Because it's, you know, we sell a product that most of our customers don't really understand. I mean they understand what it does, but […] if you are a third party that sells […] the software from [PredictiveTech] in addition, you don't create this kind of trust. And if you don't create this kind of trust in this market situation, it won't work." (Founder, PredictiveTech).

However, the move toward becoming an enabler often is associated with emancipation from the underlying platform provider, previously necessary in the role of an extender and usually ultimately leading to lower scalability. This contrasts with the strategizing trajectory away from *transformer* and toward orchestrator, both of which operate at the center of digitalized business networks (B2). The main driver through which to undertake such movement is to expand one's own business by leveraging existing hardware-based data-driven solutions to establish a platform that links additional actors (e.g., users) that previously were unconnected. In particular, the platform enables building stronger ties with existing customers, thereby collecting additional data that can be used for services and to create lock-in effects.

> "The hardware is the enabler for this whole experience and for the data that we get and this whole software platform. […] We now have a web dashboard and there you can do all these reports […]. And then in addition to that, we now have a messaging feature in the platform." (Founder, SmartLock).

4.3.3. *Strengthening the current role: "Being the star in your neighborhood"*

Besides changing one's own role to move toward the center of the business network or increase ties' strength to access additional proprietary data, we identified a third main strategizing trajectory that describes the strengthening of the current role. In some cases, the data-driven start-ups' founders perceived the current role as sufficient to reach their strategic goals and become the "star in their neighborhood". Specifically, we observed this strategizing trajectory through *enablers* and *orchestrators*. Although there is no change in network role, this third strategizing trajectory also carries implications for the data-driven start-up's operation in digitalized business networks. For instance, *enablers* that purposefully decide to remain in their role accept limited scalability and focus on specific niches (C1). Due to their strong ties with incumbent customers, they are often the target of acquisitions by incumbents. Although they cease to exist as an independent actor, the acquisition allows enablers to access resources at scale, such as financial investment or domain knowledge. In particular, access to downstream resources, such as sales staff or distribution channels, supports these data-driven start-ups' further growth and development.

> "I think, now we are in a different situation. We are not a start-up now, we are using [the acquirer], they have sales offices all over the world. […] I prefer to be part of a bigger strategy, bigger solution, bigger offering […]. And they have great connections, great brand, 112 years of reputation. […]." (Founder, PredictiveTech).

However, *orchestrators*, generally aim to grow their user base

continuously through network effects without specifically aiming to get acquired and using the incumbents' resources on a large scale to get the dominant and central actor in digitalized business networks (C2). In doing so, *orchestrators* acquire additional proprietary data sources to enrich their offerings with additional services, ultimately resulting in a winner-take-all market.

> "I think each market place has only a limited amount of space for certain types of businesses. […] And therefore is only room in the market for one. […] I would integrate more external data sources. So to get more a 360 degree view what is happening in the market rather than just [our] data. And I think that increasing that knowledge base [is suitable] to develop services that sit on top. […] To basically become an essential tool in a consumer's life and an essential tool being the ability to help them more than anyone else can." (Founder, ComplaintPlatform).

4.3.4. Failure: *"Don't boil the ocean"*

Besides the three main strategizing trajectories, we also identify an additional trajectory that is considered with a high probability of failure (D). The diagonal movement from the *extender* to the *orchestrator* requires a change not only in the strength of ties, but also in the network position. However, coming from the extender with only weak ties to customers and a peripheral network position, it was difficult to approach both at once, as such a move is accompanied with considerable change management and new capabilities, e.g., governing value across all actors on the digital platform. Instead of focusing first on building strong ties with targeted customer groups, then thinking about how to scale, the founders wanted to scale and build strong ties without offering a solution that could be scaled.

> "So we were trying a bit more than a year and we had some costumers but […] it couldn't allow us to scale very well. […] And so maybe we should have targeted directly some IT guys, or maybe head of projects to implement directly inside the whole team instead of focusing single users." (Founder, CommunicationApp).

Focusing on growth while building strong customer ties is a challenging task for founders and often can result in failure. Therefore, the various strategizing trajectories should be approached in a rather focused and sequential manner.

> "You will see that there are a lot of different avenues that they could have expanded upon. […] But when you take a look, as a start-up you have to focus on one thing because you do not want to boil the ocean." (Founder, FinApp).

5. Discussion and implications

Previous literature in IMP focuses primarily on the analysis of start-ups' strategizing and network roles in non-data-driven contexts (Aaboen et al., 2016; Baraldi et al., 2019), raising the question whether and how data-driven start-ups may strategize differently in specific network roles. Therefore, we apply theories-in-use and multiple case study research in order to investigate 23 data-driven start-ups through the uniquely combined lens of the ARA model and the DDBM framework, addressing research needs on the intersection of digitalization and business networks (Ritter & Pedersen, 2020). Thereby, we identify network roles, contrast them in the light of our identified contradictions, and draw dynamic strategizing trajectories of data-driven start-ups in digitalized business networks. In the following, we discuss for each implication how it contributes and relates to knowledge from extant IMP and DDBM literature. Moreover, we describe the implications of our study for the management of data-driven start-ups and also incumbents. Finally, we outline the limitations of the study and the resulting potential avenues for future research.

5.1. Theoretical implications

Our study's findings offer three main implications for academic research in IMP literature on start-ups, as well as for literature on data-driven business models and digital business strategy.

First, we contribute to IMP research on start-ups by introducing four network roles (enabler, extender, transformer, orchestrator) that are unique to the context of data-driven start-ups. This extends prior studies that examined network roles and strategizing of start-ups mainly in the physical context (Baraldi et al., 2019), and from the resource level perspective (Aaboen et al., 2016), ignoring the changes that digitalization brings simultaneously at the activity, resource, and actor levels in business networks (Pagani & Pardo, 2017). Specifically, we add to Aaboen et al. (2016) by providing an empirically grounded framework based on two distinct variables that determine data-driven start-ups' network roles and strategizing dynamics in the specific context of digitalization: (1) strength of network ties to access data as key resources and (2) the network position. While Aaboen et al. (2016) identified their network roles by placing resource interactions at the core of their attention, we emphasize that not only is the interaction itself important, but also how strong the ties within that interaction are (Elfring & Hulsink, 2003). In particular, how access to data, as a key resource, is managed in digitalized business networks comprises a key aspect of data-driven start-ups' strategizing and makes our network roles explicit, specific, and more concrete. This in-depth knowledge is key to performing the respective network role successfully (Aaboen et al., 2016) and serves as a basis to better understand the peculiarities of digitalization in business networks (Ritter & Pedersen, 2020), thereby achieving a greater contextualization of existing concepts in IMP research (Baraldi et al., 2020; Bocconcelli et al., 2020).

Second, we enrich research on start-ups by demonstrating conceptually and empirically, that widely accepted tenets in IMP literature about start-up strategizing do not hold true for data-driven start-ups in specific network roles. For example, prior IMP studies state that start-ups enter business networks at the periphery, have a weak power position relative to incumbents, and need a long duration to get established in business networks (Havenvid & La Rocca, 2017; Oukes et al., 2019; Snehota, 2011). In contrast, we show that particularly data-driven start-ups in the network role of orchestrators, which connect consumers and incumbents, can start in the center, are in a strong power position vis-á-vis incumbents, and get established in a shorter time through their network effects (Shapiro & Varian, 1999). Therefore, we demonstrate that data-driven start-ups in the network role of orchestrators, indeed, can drive other actors from the start and, thus, indicate a certain disruption potential in business networks, as they alter existing relationships or create new ones between previously unconnected actors (Heikkinen, Mainela, Still, & Tähtinen, 2007). This complements findings from market shaping literature (Nenonen et al., 2019; Storbacka, 2019) that emphasize the need to understand not only how resource linkages, i.e., relationships, can be created between actors, but how these actors can be mobilized to continuously exchange resources so that they can then ultimately act as drivers in digitalized business networks. Specifically, the combination of strong ties with incumbent actors to access data and the central network position determines network-specific resources that lead to an increase in the structural power base vis-á-vis incumbents (Kähkönen & Virolainen, 2011). However, we also demonstrate that certain tenets from IMP literature remain robust in the context of digitalized networks. For instance, extenders and enablers start at the network periphery, or transformers exhibit a long duration to get established and have a weak power position relative to incumbents in digitalized business networks. Therefore, we acknowledge that data-driven start-ups are also characterized by the liabilities of smallness and newness in those network roles, i.e., they tend to be driven by incumbents that usually are operating at the network center (Baraldi et al., 2019). Therefore, we also contribute to the literature on data-driven business models and digital business strategy by demonstrating that,

contrary to the economies of digitalization (marginal costs, perfect replication, ubiquitous availability) (McAfee & Brynjolfsson, 2017) and their strategic implications for scalability (Bharadwaj et al., 2013), not every data-driven start-up, e.g., as an enabler, can leverage them appropriately due to the network role's inherent design. However, this does not necessarily mean that data-driven start-ups that are being driven by incumbent actors are not able to succeed in digitalized business networks. On the contrary: if data-driven business model and the respective network role is aligned, data-driven start-ups are able to strategize successfully in all four network roles we identified. This is in line with findings from Diaz Ruiz, Baker, Mason, and Tierney (2020), who highlight that business model design is critical, as the technological innovation alone is insufficient to drive markets. In summary, data-driven start-ups can both drive or be driven by incumbents depending on their network role. Jaworski, Kohli, and Sahay (2000) argue that start-ups in general have the potential to be market drivers, yet this is strongly related to the founders' mental models that shape their respective network understandings. We extend and refine this insight by extending it to data-driven start-ups, finding that only those operating in certain network roles, and thus in specific founders' mental models, may be able to drive markets.

Third, we contribute a dynamic perspective to IMP literature by deriving three main strategizing trajectories that data-driven start-ups take in digitalized business networks. Although previous studies state that the dynamic component in business networks is inherent (Håkansson & Snehota, 2017) and that the strategizing efforts in deliberate trajectories are key to succeeding in complex and rapidly changing digitalized business networks (Möller et al., 2020), the dynamic perspective is not yet taken into account sufficiently in the context of strategizing (Aaboen et al., 2016; Baraldi et al., 2007). By adopting this dynamic perspective, our framework allows for explaining how data-driven start-ups move from one network role to another through their strategizing. Therefore, in the case that the desired network role is not reached yet, we uncover that many data-driven start-ups begin in the network role of extender, build strong ties to access proprietary data in the role of enabler, then finally move into the role of orchestrator in a central network position. Due to this sequence, changing network positions requires more effort and resource investments than building strong ties to access data (Håkansson & Ford, 2002). Similarly, from a strategizing perspective, it is important to secure access to key resources first, initiate knowledge sharing, and strengthen the current peripheral network position before expanding the number of ties in a more central network position (Aaboen et al., 2013). Our findings further support the common perception of the orchestrator with its digital platform as the "holy grail" and main target of strategizing in digitalized business networks (Bharadwaj et al., 2013), as this network role simply exhibits the strongest alignment with DDBM tenets. However, pitfalls also exist, like the lack of capabilities and financial support required to develop the digital platform. To sum up, data-driven start-ups should not exceed a certain magnitude of change in their strategizing efforts and instead take a step-wise approach, moving vertically or horizontally from one network role to another to increase the likelihood of achieving the desired network role and ultimately succeeding in digitalized business networks.

5.2. Managerial implications

Besides its theoretical contributions, our study provides three main managerial implications for data-driven start-ups' founders as well as for incumbents' managers.

First, our framework, comprising four network roles for data-driven start-ups, enables founders to gain insights on the different roles that data-driven start-ups can play in digitalized business networks. Specifically, founders can determine and evaluate their current network roles according to two variables (1) strength of ties to access data as key resources and (2) network position within a business network, providing guidance on which variables are critical to strategizing. Moreover, founders can assess to what extent the data-driven start-up's network position aligns with their strategic goals related to, e.g., scalability and collaboration intentions. Understanding the current network role and its distinct characteristics helps founders finding the network role that might suit their strategic goals most appropriately. Moreover, incumbents' managers can use the framework to analyze how data-driven start-ups position themselves relative to incumbents. This assessment helps incumbents' managers understand that data-driven start-ups' aims might differ from the substitution of established network actors; therefore, incumbents' managers get better insights concerning under which circumstances they should collaborate and strengthen ties with a specific data-driven start-up.

Second, our study helps data-driven start-ups' founders and incumbents' managers understand the conditions of digitalized business networks, resulting in new strategizing opportunities for start-ups that differ from the physical context. Specifically, founders and managers should realize that prior assumptions (peripheral network position, strong ties to access key resources, long embedment duration in the network, weak power position relative to incumbents) that were valid mainly in the physical context have only limited applicability to data-driven start-ups depending on their specific network role. Therefore, our structured comparison of strategizing tenets from the physical (IMP) and digital (DDBM) contexts, on the one hand, provides founders with a qualitative measurement tool with which to assess the disruption potential of each network role in digitalized business networks. The more DDBM tenets are confirmed, the higher the disruption potential. On the other hand, incumbents' managers can use this measurement tool to identify whether the data-driven start-up could pose a threat and disrupt the incumbent's network, thereby eliciting the possibility of initiating appropriate countermeasures in a timely manner.

Third, by using our framework, data-driven start-ups' founders and incumbents' managers can comprehend how data-driven start-ups dynamically change their network role in a digitalized business network. Founders should be aware that adaptations of the network role as strategizing trajectories include fostering their current role, changing dependency on key actors through ties, or altering the network position of their start-up. However, considering that investing in both strong tie development and network position simultaneously is challenging, founders should focus on changing one variable first. This approach leads to the necessity of taking indirect paths via other network roles. As data-driven start-ups develop dynamically in digitalized business networks, incumbents' managers, therefore, should observe the network roles long-term. Our framework helps incumbents' managers recognize typical strategizing trajectories of data-driven start-ups, specifically the often used trajectory from the enabler to orchestrator, to assess potential competitive threats or collaboration opportunities.

5.3. Limitations and future research

This research provides novel insights into data-driven start-ups' network roles and their strategizing, but like any research project, our study has several limitations, providing fruitful avenues for further research.

First, we interviewed the founders at only one particular point in time and applied a retrospective approach, incurring the risk of memory loss among informants and ex-post rationalization of strategic steps, which might result in reliability problems (Halinen, Medlin, & Törnroos, 2012). We addressed this issue by comparing interviewers' statements with external data from Crunchbase, social media, or press articles, and by giving each interviewee the opportunity to reflect and provide feedback on our written case studies. Further research could track start-ups from their foundation and interview founders multiple times to generate longitudinal data. This procedure might offer additional insights about strategizing and the underlying reasons.

Second, our findings were based only on founders' subjective views

and their own sense-making during their data-driven start-ups' development. Self-perceptions can differ from reality, as other actors might have a different perspective on network positions and also network roles of respective data-driven start-ups, creating new unique boundaries of digitalized business networks shaped by their own understandings and meanings (Guercini & Medlin, 2020). Therefore, the integration of multiple network actors, such as incumbents' managers or venture capitalists, also might offer fruitful lines of investigation to gain further insights on network roles and positions from different perspectives.

Third, to the best of our knowledge, our study is the first to identify contradictions between strategizing tenets from IMP literature on start-ups and strategizing tenets deduced from DDBM literature. However, these contradictions are not meant to be exhaustive and open interesting avenues for further research dealing with digitalization and its contradictions with prior IMP literature's findings. This applies specifically to our classification framework, for which we call for a more quantitative assessment of the two variables, e.g., between strong and weak ties to access data. The framework might further serve as a foundation for future studies from which to identify further roles or sub-types and to assign them to different phases of the start-up's development. Although these limitations must be kept in mind when considering our results and implications, we are convinced that we provide valuable insights both for theory and practice.

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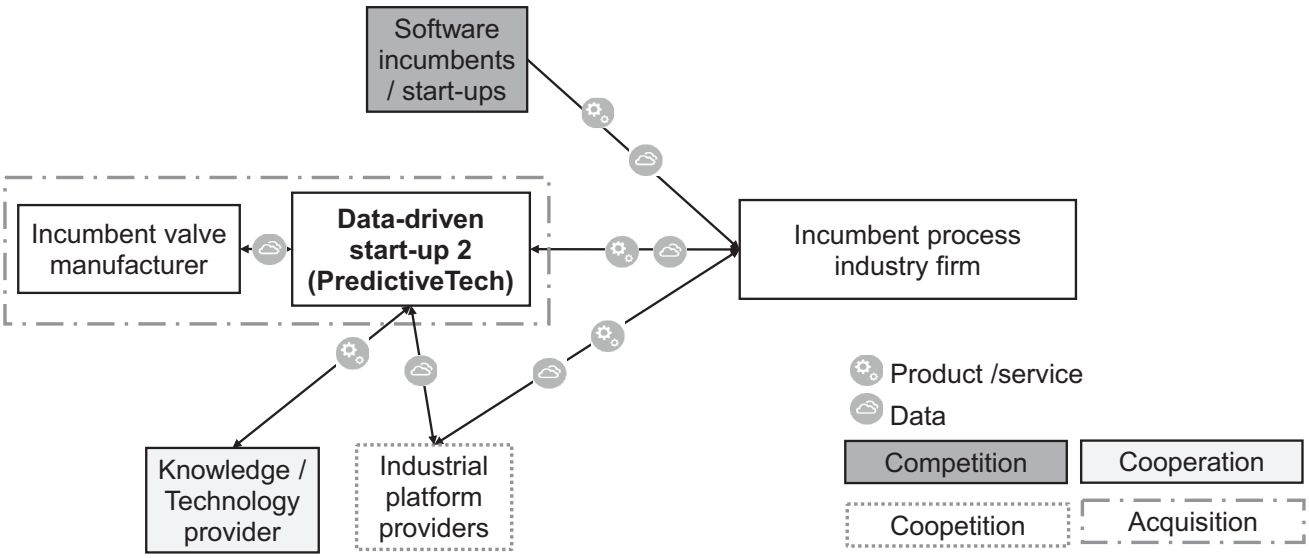
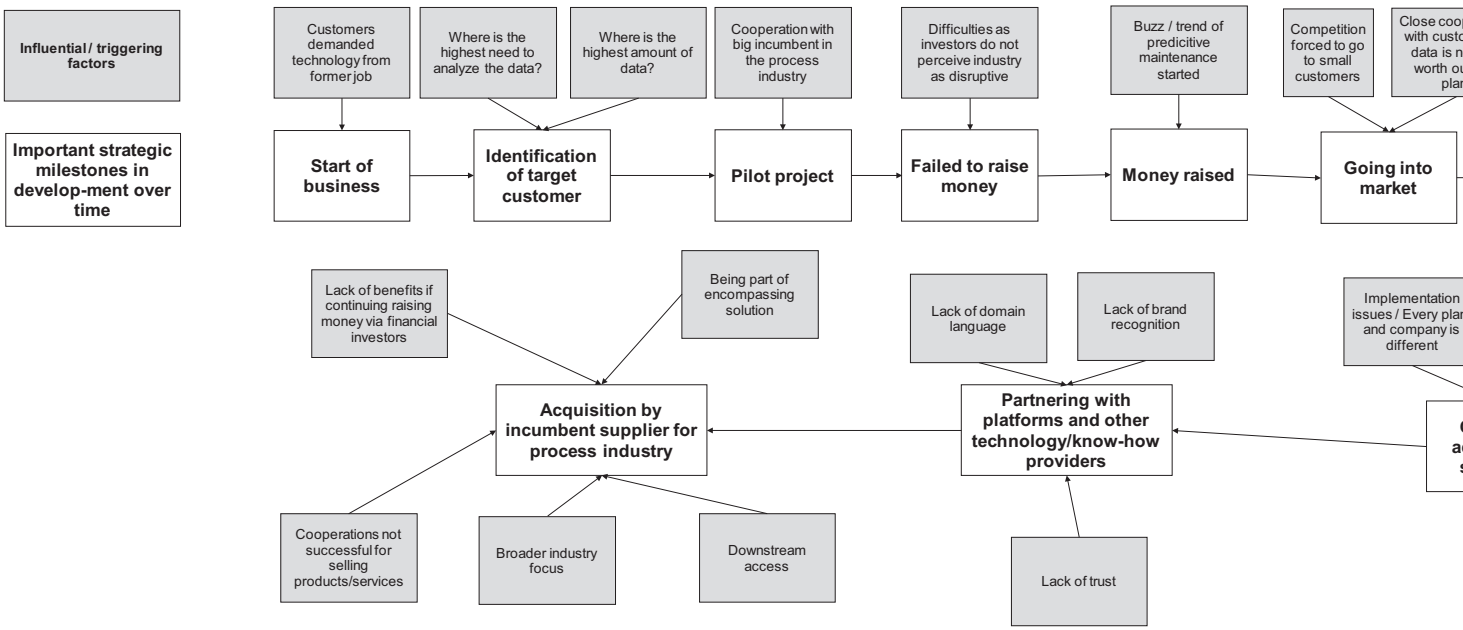
Appendix A. Interview guideline

Introduction	• *Brief introduction of the interviewer* • *General information about the interview* • *Information about the interview process*
Topic	**Main questions**
Founder's personal background and description of the business idea, business model and main stakeholders	• Could you briefly introduce yourself and tell us what background you have? • Could you please shortly describe the business idea of your start-up? • What triggered you to start your own business? • Could you please describe the main customer group? • Who is/are your main competitor/s? (Physical- vs data-oriented?) • To what extent do you see any incumbent physical firms as competitors? • Where do you get the data from?
Explanation of the initial strategy, later strategy pivots and associated trigger events	• Tell me about how you go into the market? • What are the underlying reasons for your strategy choice? • What is the goal you (personally) really have (related to the start-up / founder)? • When you entered the market, to what extent did you care about the other actors? • To what extent did you think about incumbents? • When you entered the market, to what extent did you perceived the market as a system?
Elaboration on their network role in the past, the present and the future	• How did you position yourself within your value chain / ecosystem at the beginning? • How would you describe your role in this system? • What major hurdles and changes have occurred since the foundation of your start-up? Why? • How did you adjust your start-up to fit these changes? • What are the plans for your start-up in the future?
End	• If you rethink the development of the strategy of your start-up, what would you do differently? • This brings us to the end from my side. Do you have any further comments or questions? Do you want to add anything? Is there anything important that we haven't talked about in the course of the interview? • Then let me thank you for taking part in the interview. Your input has been extremely helpful for us. If you wish to add something later, please do not hesitate to contact us by phone or e-mail. I wish you a pleasant day. Goodbye!
Probes and follow-up questions	• What do you mean by…? Can you elaborate on this? • Why is that? Could you provide an example?

Appendix B. Exemplary network constellation and plot of strategic milestones of the data-driven start-up PredictiveTech from our sample.

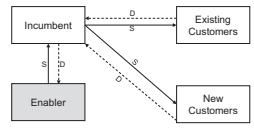
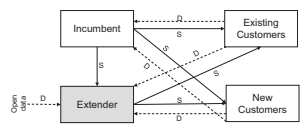
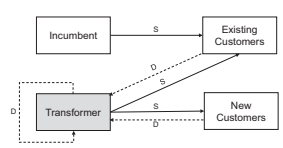
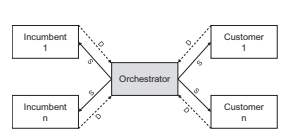




Appendix C. Evaluation of rigor

Following the criteria for rigor evaluation proposed by Lincoln and Guba (1985) and Zeithaml et al. (2020), we ensured our study results' credibility, transferability, dependability and confirmability. To increase credibility in our study, we conducted our interviews with three researchers present. While one researcher mainly conducted the interview, asking probing questions, the other two researchers took detailed notes and were allowed to ask clarifying questions at the end in case something was overlooked during the interview. In particular, the later discussion of the interviews and the comparison across participants helped to establish a shared, complete, and credible understanding of what was said (Tidström & Rajala, 2016; Zeithaml et al., 2020). By including data-driven start-ups with different status levels and ages, and without a regional or cultural focus, we ensured the results' transferability and external validity (Zeithaml et al., 2020). Overall, our sample is based on 11 data-driven start-ups from Europe, eight from North America and four from mainly developing countries in Asia, South America and the Middle East. To ensure dependability and, thus, reliability in our data, we asked three independent judges who were familiar with qualitative research methods, but not involved in our research project, to assign a random sample of five cases to the specific network roles and strategizing trajectories that we identified. We computed inter-judge agreement among the researchers using the proportional loss reduction method by Rust and Cooil (1994), generating a value of 0.84 for the network roles and 0.98 for the strategizing trajectories, both well above the threshold of 0.7 recommended for exploratory research (Nunally & Bernstein, 1978). We also shared individual case descriptions, including network constellations with the interviewees, to validate our analyses' accuracy, asking them whether the conclusions are consistent with their views (Elfring & Hulsink, 2007; Zeithaml et al., 2020). We invited further remarks and discussions to increase our results' objectivity by this member check approach.

Appendix D. Overview of network role analysis based on the ARA and DDBM framework

Network role	ARA framework combined with DDBM components			Business Network map (S = Solution; D = Data)	Alias names of data-driven start-ups from sample
	Activities	Resources	Actors		
Enabler	Offering Enabling incumbent customers with huge historical data sets to work more effectively or efficiently (e.g., predictive maintenance, sales analytics). Key activity Processing, analyzing, and visualizing data from incumbent companies (e.g., analyzing robot data to make them ready for smart interactions with humans). Revenue model Mostly subscription-based revenue model. Cost structure Low specific cost advantage due to complex data acquisition and lack of scalability.	Key resources · Proprietary customer data from · incumbent · Data analytics skills · Deep industry and · process domain · knowledge · Trustful and close relationship · with incumbent customer	Customer segment Incumbent customers in B2B sectors. Others Third parties with non-data-driven solutions as competitors or as partners (e.g., consulting firms).		TrendTech PredictiveTech MonitoringTech SalesTech SearchTech RoboTech CloudTech MarketingTech PsychologyTech AnalyticsTech
Extender	Offering Extending incumbent's offerings with new functionalities (e.g., social media data about disruptions for routing service applications). Key activity Collecting, acquiring, and analyzing data from open APIs and own customers (e.g., analyzing freely available legal texts to provide incumbents with implications). Revenue model Mostly freemium-based revenue model. Cost structure High specific cost advantage due to simple data access and high scalability.	Key resources · Free available data from open · APIs · Data generated through · customer's usage · Data analytics skills · Providing an platform- or · service agnostic solution · Data-driven platform solution · from incumbent	Customer segment Mix of individual end-users in B2C sectors and specific B2B sectors. Others · Incumbent platform provider · (technological or service · basis) · Open data provider		CommunicationApp MobilityApp GovApp FinApp
Transformer	Offering Enriching incumbents' non-data-driven offerings with digital components (e.g., smart and connected door lock), thereby transforming and substituting incumbent actors. Key activity Collecting, processing, and analyzing data from customers using the physical device to create complementing data-driven services. Revenue model One-time sale with regular subscription-based fees for additional data-driven services. Cost structure High specific cost advantage due to marginal data acquisition via physical devices at the customer end and economies of scale of large contract suppliers manufacturing the hardware components.	Key resources · Self-generated/ self-· collected · data sets · Data analytics skills · Knowledge concerning the · digitally-enabled product or · service · Tangible resources (raw · materials or end product)	Customer segment Mix of individual end-users in B2C sectors and incumbent companies in specific B2B sectors. Others · Competing incumbent · Production partners for physical · product (hardware supplier)		SmartLock SmartImage
Orchestrator	Offering Orchestrating and connecting actors previously unconnected via providing a digital platform. Key activity Acquiring, aggregating, processing,	Key resources · Proprietary customer data · Other data sources (e.g., · free available)	Customer segment Mix of individual end-users in B2C sectors and incumbent companies in specific B2B sectors.		ComplaintPlatform AIPlatform CarePlatform MRPPlatform FinancialPlatform SpeechAIPlatform GiftPlatform

(continued on next page)

(*continued*)

Network role	ARA framework combined with DDBM components			Business Network map (S = Solution; D = Data)	Alias names of data-driven start-ups from sample
	Activities	Resources	Actors		
	and analyzing data from a large user base, thereby generating network effects by enabling mediation and exchange between different / new actors (e.g., end-consumers with incumbent companies). Revenue model Transaction-based revenue model, charging typically only one actor group. Cost structure High specific cost advantage after reaching critical mass, resulting in the ability to grow at scale and marginal costs by exploiting network effects.	· End-user interface · Data analytics skills			

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